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Swimmer selection optimization strategy research based on SPSS factor analysis

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ABSTRACT

Swimming is a sport that lays equal stress on endurance and technique, sound technique is guarantee of scientific exertion that makes contribution to swimming technique rationality and improvement direction. Utilize factor analysis method and integer programming model method; make application of mathematical model into competitive swimming. In research process, it respectively from athlete perspective adopts factor analysis method providing swimming strategy for athlete, from coach perspective utilize integer programming finding out optimal athletes assignment scheme and competition best total score; Make improvement based on precedence algorithm, apply sensitivity analysis, on the condition that optimal solution not changing, get athletes assignment performance intervals. Through this paper's research methods, analysis routes and research results, it provides reasonable suggestions and theoretical basis for swimming technique.

Key words: Factor Analysis Method, integer programming, sensitivity analysis, swimming competition

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INTRODUCTION

Swimming develops up to today, with every country swimming theories and technical research increasing improvement, training ways become more and more scientific, every country excellent swimmers' competitive levels has been widely improved, competition victory or failure tend to be a moment affair [1]. Modern swimming has already become not just athlete physical ability, speed and technical competition; its competition result has slightly great correlations with competition strategy to great extent. So-called competition strategy, its essence belongs to mathematical planning problem. Apply modern mathematical research method into competitive sports, it starts since 1970s; American mathematician T.B.keller has established a mathematical model in 1973 for medium and long distance runners training that achieved remarkable results [1, 2]. Meanwhile, Ayers has combined mathematics, mechanics and computer with discus and improved throwing technique. Optimal control theory has been developing after Second World War; its basis is state-space concept. In 1960s, with digital computer technique and space technique rapidly development, driving by dynamic system optimization theory, optimal control theory starts to take shape as an important science branch [3-5]. Develop up to today; it has already achieved remarkable results in systematical engineering, space technique, economic management and other multiple fields. Optimal control theory is according to targets features, on the specified permissible control condition, let it operate as requests and make targets arrive at optimal value [6, 7]. Its mathematical essence is a functional extreme value problem, is a variation problem under a group of constraint conditions.

Modern competitive sport is not just a movement but a comprehensive strength competition that combines physiology, psychology, mechanics, mathematics and other methods into one. Swimming as a water movement, is a lower energy transformation efficiency movement that affected by physical ability distribution, speed distribution, propulsion optimization and other factors, athlete physical ability only around 10% can be converted into advanced push force. Therefore, reasonable distribute physical ability and propulsion become the crucial problem.

For competitive swimming, lots of problems have also been emerged that waited to be solved [8-10].

Factor analysis refers to statistical technique that research extracts common factors from clusters of variations. It was first put forward by British psychologist C.E. Spearman. Integer programming was formed into an independent branch after R.E. Gomory proposed cutting plane method; it has been developed into many methods to solve all kind of problems in 30 more years. With social science theory continuously development, current relative theories are in urgent need of blending in natural science, modern information technology. This research applies factor analysis method and integer programming model in researching competitive swimming problems with expectation of deep solving relative problems, especially in sports field.

SWIMMING PERFORMANCE INFLUENCE FACTORS FACTOR ANALYSIS MODEL

Factor analysis method principle

Factor analysis is a way that tries to organize original multiple certain correlated indicators (such as p indicators) again into a group of new mutual independent comprehensive indicators to substitute original indicator. Common factors generate variance structure, and special factors explain every variable variance. The purpose is to make reasonable explanation as much as possible of original variables correlations and use it for simplifying variables dimensions and structure.

Factor analysis starting point is variable relative coefficient matrix, on the premise that less information loss, synthesize multiple variables (these variables are required to have strong correlations so as to ensure it can extract common factor from original variable) into a few comprehensive variables to research overall each aspect information multiple statistical method, and the few comprehensive variables represent information cannot overlap that variables are independent from each other, factor analysis dissolves original observation variables into common factor and special factor two parts. Factor model as following:

$$X_i = a_{i1}F_1 + a_{i2}F_2 + ...a_{im}F_M + \varepsilon_i \quad (m \le p) \tag{1}$$

Among them i=1, 2, …, p, m that $X = AF + \varepsilon$ $F_1, F_2, ...F_m$ is called common factor, is an unobservable variable, $A = (a_{ij})_{p\times m}$ is called factor loading matrix, a_{ij} represents the i variable loading in the j factor, ε_i is special factor that is a part that cannot be included by previous m pieces of common factors, and meet $Cov(F,\varepsilon) = 0$, F, ε are uncorrelated.

Factor analysis is factor model focuses on a few unobservable potential variables (that is common factor) and abandon special factor. If the first main common factor F_1 cannot represent original P pieces of indicators information, then consider to select the second common factor F_2 that is to select the second linear combination. In order to effective reflect original information, F_1 known information is unnecessary to appear in F_2, by that analogy, it can construct the third, fourth... the p common factor. General steps of factor analysis:

(1) Similar to principal component analysis, calculate $\overline{x_k}$ and $s_k (k, j = 1,2....,m)$, establish basic equations.
(2) Use principal component analysis method to determine factor matrix A.
(3) Varian orthogonal rotation, extreme variable coefficient (tend to 0 or 1 as much as possible)
(4) Get factor score function, calculate sample factors scores.

Model establishment

This paper consults documents and gets relative indicators data, refer to Table 1.

Table 1: 2012 London Olympic Games every country athlete's 1500 meter free stroke partial indicators data

\	0-300	300-600	600-900	900-1200	1200-1500
China	172.63	175.52	176.17	176.32	170.38
Canada	174.12	176.72	177.7	177.69	173.4
Tunisia	175.61	177.85	177.32	177.07	172.46
South Korea	173.67	177.09	179.32	181.45	179.08
Italy	177.63	178.3	179.24	179.46	177.29
America	178.71	180.2	179.13	178.27	176.68
Poland	177.75	180.02	179.59	179.93	177.03
Britain	178.41	180.99	180.72	181.48	179.16

Factor analysis hypothesis: Each common factor is independent from each other, special factors are also independent from each other, common factors and special factors are independent from each other.

Apply SPSS software Linear process in carrying out factor analysis of data, firstly make KMO test and Bartlett test on data, carry out factor analysis of observation sample data whether suitable or not, and then further get correlated coefficient matrix as well as its feature values, contribution rations as well as accumulation contribution ratios and so on.

Table 2: KMO and Bartlett test a

Sampling sufficient degrees Kaiser-Meyer-Olkin measurement		.705
Bartlett sphericity degree test	approximate to chi-square	49.359
	df	10
	Sig.	.000
a. Based on correlation		

From Table 2, it is known that KMO value＝0.705, Sig=0.00001. According to statistician professor Kaiser provided criterion, KMO＝0.705>0.5 is relative proper for factor analysis; Sig=0.00001<0.05 indicates that through Bartlett spheroid test prove that its correlation matrix is not a unit matrix, factor model is suitable.

Reuse SPSS software making factor analysis of data, get following results that all original variables general statistical description (Table 3), including average number $\overline{x}_i$, standard deviation σ_{X_i} and analytic case number, explanatory total variance refers to Table 4.

Table 3: All original variables general statistical description information

\	N	Minimum value	Maximum value	Average value	Standard deviation
V2	8	172.63	178.71	176.0663	2.36971
V3	8	175.52	180.99	178.3363	1.91555
V4	8	176.17	180.72	178.6487	1.46471
V5	8	176.32	181.48	178.9588	1.94099
V6	8	170.38	179.16	175.6850	3.22361
Valid N(list state)	8				

Table 4: Explanatory total variance

Factor	Initial feature value			Extract square sum and input		
	Total	Variance %	Accumulation %	Total	Variance %	Accumulation %
1	4.038	80.768	80.768	3.993	79.868	79.868
2	.880	17.602	98.369	.889	17.786	97.654
3	.061	1.227	99.596			
4	.015	.298	99.894			
5	.005	.106	100.000			
Extract method: generalized least square method						

A common factor number extract principle is common factor corresponding feature value goes beyond 1, accumulated contribution ratio>85% previous m pieces of common factors. Feature value can be regarded as representative common factor influence strength indicator in some extent, if feature value is less than 1 that indicates the common factor's explaining power is not bigger than average explaining power from one directly introduced original variable, therefore generally can use feature value above 1 as introduced criterion. While first common factor feature root is 3.993, it explains original indicator 79.868% information; the second, third, fourth common factor feature roots all less than 1, but the first, second common factor explain original indicator 97.654% information. According to common factor numbers extract principle, only needs to extract the first, second common factors (Table 5).

Table 5: Correlation coefficient matrix table

\		V2	V3	V4	V5	V6
V2	Pearson correlation	1	.943**	.741*	.402	.590
	Significance(two sides)		.000	.036	.324	.123
	N	8	8	8	8	8
V3	Pearson correlation	.943**	1	.829*	.550	.677
	Significance(two sides)	.000		.011	.158	.065
	N	8	8	8	8	8
V4	Pearson correlation	.741*	.829*	1	.906**	.961**
	Significance(two sides)	.036	.011		.002	.000
	N	8	8	8	8	8
V5	Pearson correlation	.402	.550	.906**	1	.951**
	Significance(two sides)	.324	.158	.002		.000
	N	8	8	8	8	8
V6	Pearson correlation	.590	.677	.961**	.951**	1
	Significance(two sides)	.123	.065	.000	.000	
	N	8	8	8	8	8
***. It is significant correlated in .01 horizontal(two sides).*						
**. It is significant correlated in 0.05 horizontal(two sides).*						

According to above data, draw out feature root screen plot figure (as Figure 1), combining feature root curve inflection point and feature root value.

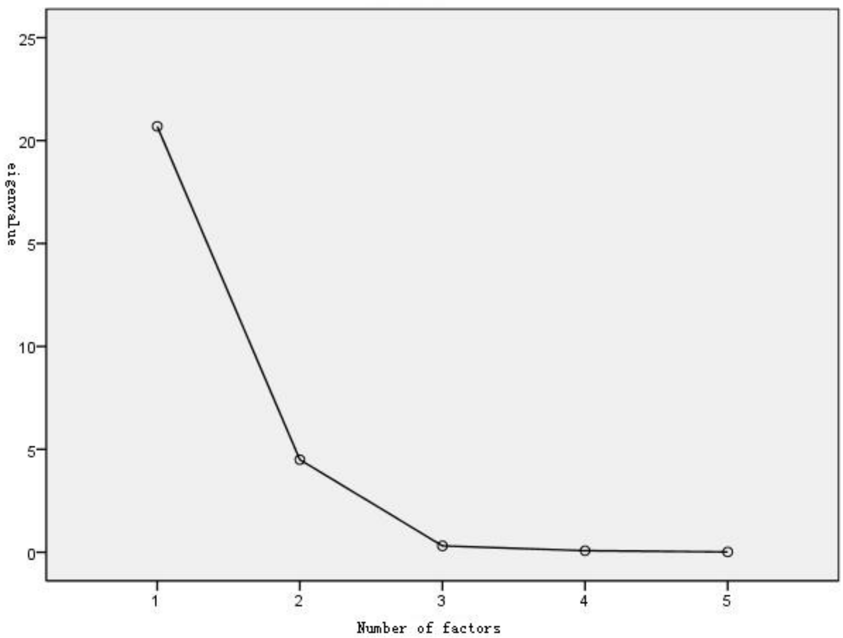

Figure1: Feature root screen plot

From Figure1, it can get first feature value and second feature value have larger change range, and can consider to take previous two factors as common factors to carry out factor analysis.

Common factor variance ratio (Table 6) evaluation indicator common degree is 0.85 bigger than all indicators that indicate model basically explains every evaluation indicator all variance and no need special factors.

Table 6: Common factor variancea

\	Initial	Extract
V2	.963	.988
V3	.949	.966
V4	.993	.998
V5	.982	.990
V6	.972	.981
Extract method: generalized least square method		
a. In iteration, it comes across one or many common factors estimation that above 1.It should be cautious when explaining solution that gets.		

Factor score coefficient matrix (Table 7) that is factor analysis final result. Through the coefficient matrix, it can express common factors as each evaluation indicator linear combination.

Table 7: Factor score coefficient matrix

\	Factor	
	1	2
V2	.099	.859
V3	.039	.233
V4	.692	-.090
V5	.139	-.620
V6	.078	-.170
Extract method: generalized least square method		

From that, it can get the first and second common factors expressions:

$$Z_1 = 0.099 * stdx_1 + 0.039 * stdx_2 + 0.692 * stdx_3 + 0.139 * stdx_4 + 0.078 stdx_5 \tag{2}$$

$$Z_2 = 0.859 * stdx_1 + 0.233 * stdx_2 - 0.09 * stdx_3 - 0.62 * stdx_4 - 0.17 stdx_5 \tag{3}$$

Total score function:

$$Z = \left(79.868 Z_1 + 17.786 Z_2\right) / 97.654 \tag{4}$$

Among them, $stdx_i \, (i = 1,2,3,4)$ represents evaluation indicator variable after standardization:

$$stdx_i = (x_i - \overline{x_i}) / \sigma_{x_i} \, (i = 1,2,3,4)$$

Total score function after simplifying:

$$Z = 0.2374 * stdx_1 + 0.0743 * stdx_2 + 0.5496 * stdx_3 + 0.0008 * stdx_4 + 0.0328 stdx_5 \tag{5}$$

Due to factor analysis model coefficient matrix reflects correlation extent between original variable and common factors, according to score expressions after simplifying, it can get that the first phase and the third phase have larger coefficients, therefore athlete in 0---300m, 600m---900m such two swimming journey, it cannot loosen and speed cannot too slow, especially in 600-----900m such phase swimming journey, athlete speed should be fast, impulse in other phases' swimming journey doesn't need to be so fiercely so that can improve athlete swimming performance.

INTEGER PROGRAMMING MODEL

Integer programming

0-1 programming is a kind of special pure integer programming. Solve 0-1 programming implicit enumeration method has no need to use simplex method solving linear programming problems. Its basic thoughts start from all variables equal to 0, successively appoint some variables into 1 till get a feasible solution and regard it as current best feasible solution. Hereafter, successively test variables equal to 0 or 1 combination so that let current best feasible solution get continuously improvement, finally get optimal solution. Implicit enumeration method is different from exhaustion method, it don't need to enumerate all feasible variables combinations one by one. Through analysis, judging, it eliminates lots of variables combinations as optimal solution possibility. So they are implicit enumerated. Implicit enumeration method essence is also branch and bound method.

Model establishment

Select 4 people from 7 athletes to organize one relay team, every people with one swimming posture and 4 people take different swimming postures so that make relay team get best results(as Table 8). It can use 0-1 variables express one athlete is chosen into relay team or not, so that establish the problem 0-1 programming model, make solution with the help of ready-made mathematical software.

Table 8: 7 athletes' four swimming postures 100 meter average performance

\	A	B	C	D	E	F	G
Butterfly stroke	1'07"8	57"3	1'20'	1'15"	1'08"6	1'18"6	1'10"6
Backstroke	1'16"6	1'07"	1'07"9	1'16"2	1'08"	1'15"6	1'06"6
Breaststroke	1'25"	1'08"4	1'24"6	1'09"6	1'23"8	1'25"6	1'06"6
Free stroke	57"6	55"	59"6	57"2	1'04"4	58'2	1'03"6

Record A, B, C, D, E, F, G respectively as $i = 1,2,3,4,5,6,7;$ Record butterfly stroke, backstroke, breaststroke, free stroke respectively as swimming postures, record athlete i the j swimming posture 100meter best performance as $c_{ij}(s)$, then Table 8 can express as Table 9.

Table 9: 7 athletes' four swimming postures 100 meter average performance

c_{ij}	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
$j=1$	67.8	57.3	80	75	68.6	78.6	70.6
$j=2$	76.6	67	67.9	76.2	68	75.6	66.6
$j=3$	85	68.4	84.6	69.6	83.8	85.6	66.6
$j=4$	57.6	55	59.6	57.2	64.4	58.2	63.6

Bring into 0-1variable x_{ij}, if select athlete i to participant swimming posture j competition, record $x_{ij} = 1$, or else record $x_{ij} = 0$.

As following: $x_{ij} = \begin{cases} 1, athleteise \quad lectsswim \quad \min \quad gposture \\ 0, athleteido \quad esn\,'tselectswi \quad m \min \quad gposture \end{cases}$.

With requests of organizing into relay team, x_{ij} should meet below conditions:

Every athlete can only be selected one of four swimming postures (2) Every swimming posture can only have one athlete be selected.

Then it has:

$$\sum_{j=1}^{4} x_{ij} \le 1(i = 1,2,.....7)$$

$$\sum_{i=1}^{7} x_{ij} = 1(j = 1,2,...4)$$

Therefore, when athlete i is selected with swimming posture j, use $c_{ij}x_{ij}$ showing its performance, relay team total performance can be expressed as :

$$z = \sum_{j=1}^{4}\sum_{i=1}^{7} c_{ij} \bullet x_{ij} \, (i = 1,2,...4,\ j = 1,2,...7)$$

To sum up, swimming team's relay team athlete's selection problem 0-1 programming model can be described as:

$$z = \sum_{j=1}^{4}\sum_{i=1}^{7} c_{ij} \bullet x_{ij} \, (i = 1,2,...4,\ j = 1,2,...7)$$

$$s.t.\begin{cases} \sum_{j=1}^{4} x_{ij} \le 1(i = 1,2,.....7) \\ \sum_{i=1}^{7} x_{ij} = 1(j = 1,2,...4) \\ \quad x_{ij} = \{0,1\} \end{cases}$$

Establish target function as following:

$$\min z = 67.8x_{11} + 76.6x_{12} + 85x_{13} + 57.6x_{14} + 57.3x_{21} + 67x_{22} + 68.4x_{23} + 55x_{24} + 80x_{31} + 67.9x_{32} + 84.6x_{33} + 59.6x_{34} + 75x_{41} + 76.2x_{42} + 69.6x_{43} + 57.2x_{44} + 68.6x_{51} + 68x_{52} + 83.8x_{53} + 64.4x_{54} + 78.6x_{61} + 75.6x_{62} + 85.6x_{63} + 58.2x_{64} + 70.6x_{71} + 66.6x_{72} + 66.6x_{73} + 63.6x_{74}$$

$$\begin{cases} x_{11} + x_{12} + x_{13} + x_{14} \le 1 \\ x_{21} + x_{22} + x_{23} + x_{24} \le 1 \\ x_{31} + x_{32} + x_{33} + x_{34} \le 1 \\ x_{41} + x_{42} + x_{43} + x_{44} \le 1 \\ x_{51} + x_{52} + x_{53} + x_{54} \le 1 \\ x_{61} + x_{62} + x_{63} + x_{64} \le 1 \\ x_{71} + x_{72} + x_{73} + x_{74} \le 1 \\ x_{11} + x_{12} + x_{13} + x_{14} + x_{15} + x_{16} + x_{17} = 1 \\ x_{21} + x_{22} + x_{23} + x_{24} + x_{25} + x_{26} + x_{27} = 1 \\ x_{31} + x_{32} + x_{33} + x_{34} + x_{35} + x_{36} + x_{37} = 1 \\ x_{41} + x_{42} + x_{43} + x_{44} + x_{45} + x_{46} + x_{47} = 1 \\ x_{ij} = 0 or 1(i = 1,2,3,4,5,6,7. j = 1,2,3,4) \end{cases}$$

Use LINGO program solving results as below Figure 2:

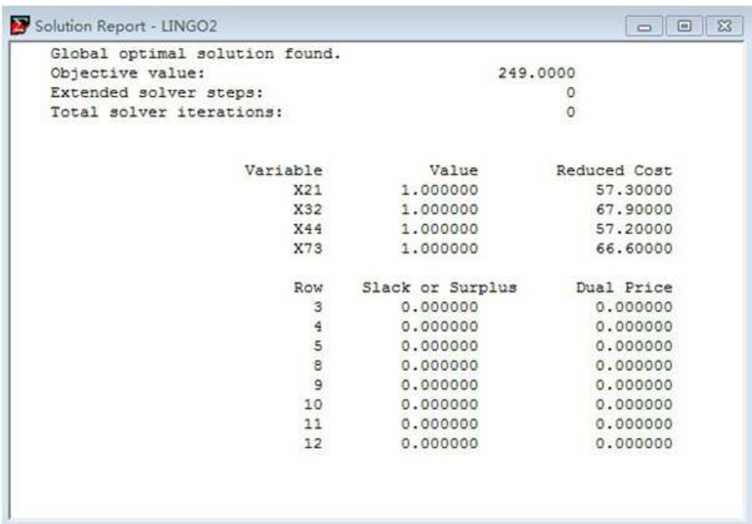

Figure 2: LINGO solution results

Apply LINGO software in calculating, it can get $x_{21}=x_{32}=x_{44}=x_{73}=1$, therefore, selected athletes and corresponding participant swimming posture types as below Table 10.

Table 10: Selection scheme

	A	B	C	D	E	F	G
Butterfly stroke		√					
Backstroke			√				
Breaststroke							√
Free stroke				√			

That is a competition scheme that selects athlete B to take butterfly stroke→athlete C to take backstroke→athlete D to take breaststroke→athlete A to take free stroke. At that time, competition best total score is $z = 249s$.

SENSITIVITY ANALYSIS

Value coefficient c change analysis.

(1) c_r is non basic variable x_r coefficient

Now c_r change only would influence on $\sigma_N = c_N - c_B B^{-1} N$ x_r check number, under requests to maintain optimal value, then it only needs to $\sigma_r' = c_r' - c_B B^{-1} P_r = c_r + \Delta c_r - c_B B^{-1} P_r = \sigma_r + \Delta c_r \le 0$

That is when $\Delta c_r \le -\sigma_r$, it can maintain optimal basis without changing.

(2) c_r is basic variable x_r coefficient

Now due to c_B changes, all non basic variables check numbers would change, under requests to maintain optimal value, then it needs to meet $\sigma_j' = c_j - c_B' B^{-1} P_j \le 0$.

Here record vector $\Delta c_B = (0,0,\cdots,\Delta c_r,0,\cdots,0)$, then it has $c_B' = c_B + \Delta c_B$.

From $\sigma_j' = c_j - c_B' B^{-1} P_j = c_j - (c_B + \Delta c_B) B^{-1} P_j = c_j - c_B B^{-1} P_j - \Delta c_B B^{-1} P_j = \sigma_j - \Delta c_B B^{-1} P_j \le 0$

It gets $\Delta c_B B^{-1} P_j \ge \sigma_j (\forall j, and \, x_j is nonbasic \, variable)$.

From that, it can get optimum basis unchangeable Δc_r value range.

Record $B^{-1} A = (a_{ij}')$, record basic variable x_r code in base as s, then $\Delta c_B B^{-1} P_j = \Delta c_r a_{sj}'$, and from $\Delta c_B B^{-1} P_j = \Delta c_r a_{sj}' \ge \sigma_j$, it can get.

If $a_{sj}' > 0$ then $\Delta c_r \ge \sigma_j / a_{sj}'$; If $a_{sj}' < 0$ then $\Delta c_r \le \sigma_j / a_{sj}'$; If $a_{sj}' = 0$ then obviously $\Delta c_r a_{sj}' \ge \sigma_j$ is true;

So that it gets optimal basis unchangeable Δc_r value range as: $\max_j \{\sigma_j / a_{sj}' \mid a_{sj}' > 0\} \le \Delta c_r \le \min_j \{\sigma_j / a_{sj}' \mid a_{sj}' < 0\}$

If value coefficient c changes, then it not meet optimal condition any more (appear positive check number), then it needs to continue to make iteration solution by simplex method.

Use LINGO can get above 0-1 programming sensitivity analysis (as Table 11)

Table 11: Sensitivity analysis

Objective Coefficient Ranges			
\	Current	Allowable	Allowable
Variable	Coefficient	Increase	Decrease
X11	67.80000	INFINITY	7.900000
X12	76.60000	INFINITY	8.700000
X13	85.00000	INFINITY	17.10000
X14	57.60000	0.6000000	0.4000000
X21	57.30000	7.900000	INFINITY
X22	67.00000	INFINITY	1.700000
X23	68.40000	INFINITY	3.100000
X24	55.00000	1.700000	7.900000
X31	80.00000	INFINITY	20.10000
X32	67.90000	0.1000000	1.300000
X33	84.60000	INFINITY	16.70000
X34	59.60000	INFINITY	2.000000
X41	75.00000	INFINITY	15.50000
X42	76.20000	INFINITY	8.700000
X43	69.60000	INFINITY	2.100000
X44	57.20000	0.4000000	INFINITY
X51	68.60000	INFINITY	8.700000
X52	68.00000	INFINITY	0.1000000
X53	83.80000	INFINITY	15.90000
X54	64.40000	INFINITY	6.800000
X61	78.60000	INFINITY	18.70000
X62	75.60000	INFINITY	7.700000
X63	85.60000	INFINITY	17.70000
X64	58.20000	INFINITY	0.6000000
X71	70.60000	INFINITY	12.00000
X72	66.60000	1.300000	2.100000
X73	66.60000	2.100000	INFINITY
X74	63.60000	INFINITY	7.300000
Right hand Side Ranges			
Row	Current	Allowable	Allowable
1	RHS	Increase	Decrease
2	1.000000	INFINITY	1.000000
3	1.000000	0.0	0.0
4	1.000000	INFINITY	0.0
5	1.000000	0.0	1.000000
6	1.000000	INFINITY	1.000000
7	1.000000	INFINITY	1.000000
8	1.000000	1.000000	0.0
9	1.000000	0.0	0.0
10	1.000000	0.0	1.000000
11	1.000000	0.0	1.000000
12	1.000000	1.000000	0.0

From Table 11 results , it is clear that when athlete A performance changes from 57.2s to 58.2s , selection that not participating any one sport is not changing, when athlete B performance changes from 47.1s to 56.7s , butterfly stroke participating selection would not change, when athlete C performance changes from 66.6s to 68.0s , backstroke participating selection would not change, when athlete G performance changes from 64.5s to 67.9s , breaststroke participating selection would not change.

CONCLUSION

Applied factor analysis method, it got total score expressions; finally put forward reasonable suggestions to athlete. Utilized integer programming model (0-1), it made suggestions about coaches athletes selection. Used sensitivity analysis in improving integer programming, let selecting athletes' performance extending from single number to a performance interval, avoided athletes being missed in selection due to special status. Model generalization performance was also very strong, it not only could be applied into Olympic Games swimming selection, but also could promote to any selection competitions. This research combined swimming and optimization theory, it provided new thoughts for swimming strategy researching; its results have great significance in swimming training and strategy arrangements.

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