Optimizing channel cross-section based on cat swarm optimization
Dong Liu, Yuxiang Hu, Qiang Fu and Khan M. Imran

ABSTRACT
Optimal design of channel cross-section is an important task in the hydraulic design of open channels. The traditional methods and models which neglect the frost heave are trial procedures and may result in failure of channels in design of irrigation channels. To improve the total cost, reliability and effectiveness, the model which is used in this study, is not only minimizing the cost of land acquisition but also the cost of concrete lining considering cost as the objective function. The constrained optimization model which considers values of thickness of channel concrete slab constraint simultaneously along with the objective of minimization of cost is propounded and solved using a recent global optimization technique, namely cat swarm optimization (CSO). The optimized channel section not only satisfies the optimal hydraulic cross-section but guarantees the safety and stability of the side walls so that both the amount of the concrete lining and the land acquisition are optimized. Finally, we take a main channel of Qinghe Irrigated Area of Farm 853 in Heilongjiang Province as a study area. The results obtained using the CSO approach are satisfaction and the method can be used for reliable design of artificial open channels. Furthermore, we compare the CSO algorithm with a genetic algorithm (GA) and the particle swarm optimization (PSO) to verify the effectiveness of the cat swarm algorithm in the channel section optimization.

Key words | cat swarm optimization algorithm, cross-section, frost heave, open channel

INTRODUCTION
Artificial open channels are the major conveyance systems used to deliver water. A trapezoidal section is the most common channel cross-section, which is used to convey water for irrigation districts. Computation of parameters of channel cross-section is an important task in hydraulic design of open channels. These parameters are traditionally obtained by numerical method, trial procedures (time-consuming), graphical method (low accuracy owing to its log-scale representation) or explicit equations (Vatankhah 2015). However, from a hydraulic engineering perspective, it would be preferred to have an optimal method with a reasonable mathematical model and high accuracy for designing the channel cross-section. In order to avoid loss of water and damage of frost heave, many water saving techniques and operations have been developed to promote water systems over recent decades. The design of different cross-sections of irrigation channels such as trapezoidal section, rectangular section, and triangular section has been determined by many researchers following explicit equations with lower flow error, but these equations consider only optimal hydraulic condition and neglect the cost effectiveness (Froehlich 1994). An optimization model is developed to minimize the total cost of construction and flooding probability, and the new cross-section is found to be cheaper than the traditional trapezoidal cross-section (Das 2009). The optimal design concept is used to determine the parameters of channel cross-section for
minimizing cost of fabrication. The model of uniform roughness was established firstly, which is based on minimization of lining cost, but neglect the excavation cost (Sakhuja et al. 2014). Channel concrete lining is very expensive and deteriorates with time. Therefore, the values of thickness of the channel lining structure are important for cost of construction in seasonally frozen ground regions (Li et al. 2013). However, these studies have not considered any effect of frost heaving damage and side slope stability in the model formulation, which may result in much wider channels with more serious damage in the cold field.

It is also noticed that conventional methods are used to solve the highly nonlinear optimization problems, but do not satisfy the requirement of accuracy. To solve channel design problems, researchers have used different methods, for example the Lagrangian multiplier (LM) method, sequential quadratic programming method and projected augmented Lagrangian multiplier (PAL) method (Froehlich 1994; Bhattacharjya 2006; Reddy & Kumar 2006; Das 2014). These conventional methods may require several approximations or simplifications on functions of the model, and then there is a greater necessity to explore and apply new optimization methods. The concept of swarm intelligence (SI) was first introduced by Beni & Wang (1993) to solve cellular robotic systems (Beni & Wang 1993; Dorigo et al. 1996). Since then, many swarm intelligence algorithms have been developed and applied in optimization problems across channel cross-section. For example, artificial bee colony algorithms have successfully been implemented to search for the global optimal solution to the single section optimization of the trapezoidal channels under global conditions (Kun & GuoSao 2011). Jain et al. (2004) used genetic algorithms (GA) to obtain optimal channel dimensions and found that the method of equivalent roughness estimation significantly affected the optimal cost (Bhattacharjya et al. 2004). Although the high-dimensional and non-linear multi-objective optimization algorithm has been introduced to the channel cross-section optimization, computational speed and Robustness are not efficient. Chu and Tsai have proposed a cat swarm optimization algorithm by stimulating nature behaviors of cats (Chu & Tsai 2007). In this paper, genetic algorithm and particle swarm optimization are compared with cat swarm optimization. The results show that this algorithm is able to conduct global search and local search at the same time in the process of evolution. It overcomes the phenomenon of local optimum inclination and possesses a superb rate of convergence. In addition, the tracking mode is similar to that of the particle swarm optimization, which uses the local optimization position to update the current position of the cat. The cat swarm optimization (CSO) algorithm combines two subgroups of global search and local search, enabling the simultaneous global search and local search in the process of evolution of each generation of the algorithm. This unique algorithm structure guarantees the rate of convergence of the algorithm, which can overcome such defects as local optimum inclination due to slow search speed of the genetic algorithm and the incapability of escaping from the local minimum due to the solution discrete problem of the particle swarm algorithm (Panda et al. 2011; Pradhan & Panda 2012; Tsai et al. 2012; Wang et al. 2012; Naveen Kumar & Surya Kalavathi 2014; Pappula & Ghosh 2014).

In this study, a new optimization algorithm, cat swarm optimization is proposed for channel cross-section. CSO is a high performance computational method, inspired from the natural behaviors of cats. It was introduced by Chu and Tsai in 2007. In this study, CSO is used to optimize the parameter of channel cross-section in order to reduce the cost with minimum values of thickness of channel concrete slab. However, this is the first paper in which CSO is introduced for channel cross-section.

The rest of the paper is organized as follows. In the ‘Cat swarm optimization’ section, the basic concepts of the CSO algorithm along with a flow chart are presented to include seeking mode and tracing mode. The mathematical formulation of optimum cross-section is introduced in the subsequent section. Next, the simulation result and analysis is presented, and then the following section discusses effectiveness of GA, PSO and the CSO. Finally, the conclusion is made.

### STUDY AREA

Qinghe Irrigation Area (Figure 1) belongs to Farm 853 in Sanjiang Plain which is affiliated with Hongxinglong Administration of Heilongjiang Land Reclamation. This area is located in the northeast of China and stretches between east longitude 132°53′58″—132°46′25″ and north latitude 46°43′35″. The climate is windy continental monsoon. It is
bounded with the seventh main channel in the east and adjac-ent to the sixth Precinct. It reaches to the fifth Precinct to the North and neighbors the third Precinct to the South. The annual precipitation and evapotranspiration are 579.6 mm and 1,197.8 mm respectively. There is Qinghe Reservoir in the southeast, which is the main water source supplemented by the groundwater. The reservoir control drainage area is 2,376 km²; total capacity is 9,710 million m³. It is 8.62 km wide from East to West and 10.2 km long from South to North. The irrigation area covers 60.8 km² including 27.5 km² paddy field acreage. The irrigation area has been operating for years. The efficiency of water conveyance for the irrigation channel is lower than 0.5. Due to years of major non-repair, serious seepage and siltation are found in most channels, which hold back economic progress in the irri-gation area. The irrigation area is badly in need of the water-saving renovation so as to ensure its normal operation and fully utilize the natural advantages.

**CAT SWARM OPTIMIZATION**

Chu and Tsai have proposed a new swarm optimization, i.e. cat swarm optimization (CSO), which imitates the natural behavior of cats (Chu & Tsai 2007). Cats have hunting skills and a strong curiosity for moving targets. Although cats spend most of their time resting, they always remain alert. When prey is present, cats get closer to the objective slowly and chase it very quickly. These two characteristics of resting with slow movement and chasing with high speed are represented by seeking mode and tracing mode, respectively.

**Seeking mode**

This model is used to simulate the case of the cat, which is resting, looking around and seeking the next position to move towards. In seeking mode, we define four main parameters: Seeking Memory Pool (SMP): this is the number of copies of a cat produced in seeking mode. Seeking Range of selected Dimension (SRD): this is the maximum difference between the new and old values in the dimension selected for mutation in the range of \([0, 1]\). Counts of Dimension to Change (CDC): this is the number of dimensions to be mutated in the range of \([0, 1]\). SPC is a Boolean valued variable, and indicates whether the point at which the cat is already standing will be one of the candidate points to move to. Seeking mode is described as follows.

![Location of Qinghe Irrigation Area in Heilongjiang Province.](image-url)
Step 1: Generate copies of cat\(_k\), where \(j = SMP\). If the value of SPC is true, let \(j = SMP - 1\) and return the present position as one of the candidates.

Step 2: According to CDC, plus/minus SRD percent’s of the current value randomly and replace the old one.

Step 3: Calculate the fitness values (FS) of all candidate points, respectively.

Step 4: If all the fitness values are not exactly equal, calculate the selecting probability \(P_i\) of each candidate point, shown as follows:

\[
P_i = \frac{FS_i - FS_b}{FS_{max} - FS_{min}}, \text{ where } 0 < i < j
\]  

If the goal of the fitness function is to find the minimum solution, \(FS_b = FS_{max}\), otherwise \(FS_b = FS_{min}\).

Step 5: Randomly pick the point to move from the candidate points and replace the position of cat\(_k\).

**Tracing mode**

Tracing mode is the sub-model for simulating the situation of the cat in tracing some objectives. When a cat enters into tracing mode, it moves according to its own velocity. The action of tracing mode can be described in three steps as follows.

Step 1: Compute the new velocity using Equation (2) for every dimension (\(V_{k,d}\)).

\[
V_{k,d} = V_{k,d} + r_1 C (X_{best,d} - X_{k,d}), \text{ } d = 1, 2, \ldots, M
\]  

where \(X_{best,d}\) is the position of the cat, who has the best fitness value; \(X_{k,d}\) is the position of cat\(_k\), \(C\) is a constant and \(r_1\) is a random value in the range of [0,1].

Step 2: Check if the velocities are in the range of maximum velocity. In case the new velocity is over range, make sure it is equal to the limit.

Step 3: Compute the new position of cat\(_k\) using Equation (3).

\[
X_{k,d} = X_{k,d} + V_{k,d}
\]

**Algorithm description**

CSO includes two sub models, the seeking mode and the tracing mode to solve the optimization problem. A mixture ratio (MR) is used which defines the ratio of number of cats in tracing mode to that of number of cats in seeking mode. The flow chart of the CSO algorithm is shown in Figure 2.

**OPTIMIZATION MODEL**

**Objective function**

The trapezoidal section is the most common channel cross-section, which is showed in Figure 3.
The value of flow rate $Q$ is given by Manning’s formula, that is (Das 2014)

$$Q = AC\sqrt{Ri}$$  \hspace{1cm} (4)

$$C = \frac{1}{n}R^{0.6}$$  \hspace{1cm} (5)

$$R = \frac{A}{\chi}$$  \hspace{1cm} (6)

$$A = (b + m \times h) \times h$$  \hspace{1cm} (7)

where $Q$ is the discharge (m³/s); $A$ is the wetted cross-section area, (m²); $C$ is the Chezy coefficient (m⁰.⁵/s); $R$ is the hydraulic radius (m); $b$ is the width of channel bottom (m); $h$ is the height of channel (m); $\chi$ is the wetted perimeter (m); $i$ is the longitudinal channel bed slope; $n$ is the Manning’s roughness coefficient; $m$ is the side slope of the channel. $Q$, $n$, $i$ are known, while $b$, $h$ and $m$ are design variables.

The objective function is based on minimum land acquisition cost and concrete lining cost per unit length of the channel. Land acquisition cost is presented for total crop yield in the area of the channel. The minimization of the objective function is given by Equation (8) along with a constraints Equation (9).

$$f = \min (C_1V + C_2B)$$  \hspace{1cm} (8)

Subject to

$$T = \max [T_1, T_2]$$  \hspace{1cm} (9)

$$C_2 = \frac{YP}{667}$$  \hspace{1cm} (10)

where $V$ is the lining volume of channel per m length; $C_1$ is the concrete cost per unit volume; $B$ is the width of free surface; $C_2$ is the coefficient of construction land; $Y$ is the crop yield per mu; $P$ is the unit price of crop; $T$ is the minimum value of thickness of channel concrete slab; $T_1$ and $T_2$ are the values of thickness respecting frost-heaving force and slope stability.

**Problem constraints**

The trapezoidal lined channel is generally composed of the bottom plate and the side slope. The side slope plate can be considered as the cantilever slab supported by the wall bottom whose load mainly includes earth pressure, gravity stress and frost heaving reaction force. For the sake of safety, all computations are conducted as per the shady slope in view of the fact that there is no water in the channel and the water content in the soil behind the wall is saturated. Counting the side slope plate as the sloping style retaining wall obtained by calculation of the minimum lining thickness $T_1$ greater than the anti-freeze heaving damage and the lining thickness $T_2$ under the minimum side slope stability coefficient (Li et al. 2015).

**Effect of frost heaving damage restriction**

The mechanics analysis of frost heaving damage is shown in Figure 4.

The axial pressure of any section should be:

$$N(x) = \frac{\tau_0}{2L}x^2$$  \hspace{1cm} (11)

![Figure 3](http://iwaponline.com/ws/article-pdf/16/1/219/413498/ws016010219.pdf) **Figure 3** | Geometric dimensions for trapezoidal cross-section.

![Figure 4](http://iwaponline.com/ws/article-pdf/16/1/219/413498/ws016010219.pdf) **Figure 4** | Mechanics analysis of frost heaving damage.
The bending moment shall include the eccentric bending moment $M_1$ and the bending moment $M_2$ produced by normal frost-heave force.

$$M(x) = M_1(x) + M_2(x) = \frac{\tau_0}{4L}x^2T_1 + \frac{1}{6}\tau_0 Lx - \frac{q_0 x^3}{6L}$$  \quad (12)$$

The maximum bending moment section:

$$x_0 = \frac{\tau_0 T_1}{2q_0} + \sqrt{\left(\frac{\tau_0 T_1}{2q_0}\right)^2 + \frac{L^2}{3}}$$ \quad (13)$$

The maximum tensile stress:

$$\sigma_0 = \frac{6M(x_0)}{T_1^2} \cdot \frac{N(x_0)}{T_1}$$ \quad (14)$$

Obtain the lining thickness $T_1$ which is satisfying the anti-freeze requirement by checking calculation of crack resistance condition $\frac{\sigma_0}{E_c} < \varepsilon_t$.

**Effect of side slope stability restriction**

The side slope stability analysis is shown in Figure 5. The total active earth pressure should be calculated as Coulomb's theory. The calculation formula is as follows:

$$P_a = \frac{1}{2} \gamma h^2 K_a$$ \quad (15)$$

$$K_a = \frac{\cos^2 (\varphi - \alpha)}{\cos^2 \alpha \cos (\alpha + \varphi_0) \left[1 + \frac{\sin (\varphi + \varphi_0) \sin (\varphi - \beta)}{\cos (\alpha + \varphi_0) \cos (\alpha - \beta)}\right]^2}$$ \quad (16)$$

where $K_a$ is the active earth pressure coefficient, $\alpha$ is the included angle between the wall back and the vertical curve. The sloping wall back $\alpha$ should be negative. $\beta$ is the included angle between the earth fill surface and the horizontal plane. The channel usually adopts backfill with the flat wall in the horizontal position, so $\beta = 0, \varphi_0$ is the friction angle between the back wall and filling. The inclined retaining back wall $\varphi_0 = \varphi/3$, $\varphi$ is the internal friction angle behind the wall, $h$ is the height of channel, $\gamma_s$ is the saturated soil bulk density.

The form of damage of the side wall is overturn failure (i.e. the plate $AO$ tumbles in toward the channel inside with $O$ point as the fulcrum to produce displacement destruction). Its overturn moment $M_o$ and the anti-tipping moment $M_r$ are as follows respectively.

$$M_o = \frac{1}{6} \gamma h^3 K_a \cos \varphi_0 / \cos \alpha + \frac{PL}{3}$$ \quad (17)$$

$$M_r = \frac{1}{2} m \sqrt{1 + m^2 \gamma_2 h^2}$$ \quad (18)$$

Anti-tipping safety coefficient $K = 1.1, M_r / M_o > 1.1$. The minimum value of thickness required for the side wall stability $T_2$ should be obtained (Wang 2004).

It can be seen that the side wall thickness $T$ is relevant to the soil quality, aspect and channel depth. In order to satisfy the anti-freeze requirement and the stability demand, greater values in $T_1$ and $T_2$ should be chosen. Under the condition of a certain soil texture, the side wall thickness $T$ is inversely proportional to the side slope $m$, i.e. in order to meet the needs of stability, the greater $m$ is, the smaller the required side wall thickness $T$ should be. Whereas, the smaller $m$ is, the greater the required side wall thickness $T$ should be. If $m$ is given, the required minimum thickness for the stability of the side wall can be obtained. Otherwise, the maximum $m$ value can be obtained as well.

**CASE STUDY**

The optimization model is validated by the following data extracted from the first main channel:

Discharge, $Q_d = 2.57$ m$^3$/s; longitudinal slope, $i = 1/1,500$; roughness parameters $n = 0.017$. Turfy soil, saturated soil
bulk density, \( \gamma_s = 1.95 \text{ g/cm}^3 \), internal friction angle \( \varphi = 14^\circ \), cohesive strength of soil \( c = 34.2 \text{ kPa} \), non-scouring velocity \( v_{cs} = 2.5 \text{ m/s} \), non-silting velocity \( v_{cd} = 0.4 \text{ m/s} \).

The solutions of optimal cost obtained by different solution methods are presented in Table 1. For \( b \) value ranging from 0.85 m to 2.15 m and \( m \) value ranging from 1.25 to 1.35, the critical water depths were obtained using Manning’s equation. The cost was calculated by Equation (4). It can be seen that the cost from a trapezoidal section with the CSO method is the global optimization. Obviously, the optimum is less sensitive to increase in bed width and more sensitive to increase in side slope. Table 1 shows the optimization results from the genetic algorithm, particle swarm algorithm and cat swarm optimization algorithm for which the parameters \( m, b, h \) obtained by the cat swarm optimization algorithm can minimize the lining cost and the land occupation under the condition of satisfying the optimum hydraulic section. It saves 8.2% and 10.8% construction investment compared with the genetic algorithm and particle swarm algorithm respectively with the low flow errors.

The channel geometric parameters are listed in Table 1. Therefore, \( b, m, h \) are determined by the objective function, while we optimize them by using the optimization algorithm. Figure 6 shows that the most striking parameter deciding the optimal overall cost is the wetted perimeter \( (\chi) \) and width of the channel at the water surface \( (B) \), which indicates a decreasing trend with a reduction of optimal value. The sensitivity study shows that a reduction of water depth increases the overall cost. It can be seen that there is much significant difference in optimal costs of the GA, PSO, and CSO methods.

**DISCUSSION**

The simulation is using MATLAB version 2009a for the design.

### Table 1 | Simulation results

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>( m )</th>
<th>( b ) (m)</th>
<th>( h ) (m)</th>
<th>Cost (Yuan)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>1.25</td>
<td>1.95</td>
<td>0.85</td>
<td>124.77</td>
<td>1.35</td>
</tr>
<tr>
<td>PSO</td>
<td>1.35</td>
<td>1.75</td>
<td>0.87</td>
<td>122.9</td>
<td>0.3</td>
</tr>
<tr>
<td>CSO</td>
<td>1.35</td>
<td>2.15</td>
<td>0.80</td>
<td>109.95</td>
<td>0.5</td>
</tr>
</tbody>
</table>

To solve the model using the GA, PSO, and CSO methods, the following parameters which are shown in Table 2 involve: population size of 50; max iteration cycles of 100; crossover rate of 0.8; mutation rate of 0.01; selection probability of 1/3; acceleration coefficients \( c_1 = 2 \) and \( c_2 = 2 \); minimum velocity \( (v_{min}) \) of −1 and maximum velocity \( (v_{max}) \) of 1; seeking memory pool \( (SMP) \) of 5; counts of dimension to change \( (CDC) \) of 0.2; seeking range of selected dimension \( (SRD) \) of 0.2; mixture ratio \( (MR) \) of 0.5; acceleration constant\( (C) \) of 1.

**Table 2 | Parameters setting for GA PSO and CSO**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>GA</th>
<th>PSO</th>
<th>CSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Max. iteration cycles</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.8</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Crossover</td>
<td>Two point crossover</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.01</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Mutation</td>
<td>Gaussian mutation</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Selection probability</td>
<td>1/3</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Selection</td>
<td>Roulette wheel</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>( c_1, c_2 )</td>
<td>2, 2</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>( v_{min}, v_{max} )</td>
<td>−1, 1</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SMP, CDC, SRD</td>
<td>–</td>
<td>5, 02, 0.2</td>
<td>–</td>
</tr>
<tr>
<td>MR</td>
<td>–</td>
<td>0.3</td>
<td>–</td>
</tr>
<tr>
<td>C</td>
<td>–</td>
<td>1</td>
<td>–</td>
</tr>
</tbody>
</table>

**Figure 6 | Optimal solution of GA, PSO, CSO.**

Table 3 shows the time consumption comparison of GA, PSO and CSO under different population numbers. It is thus clear that the cat swarm algorithm consumes higher...
computation time than GA and PSO. Hence there is a trade-off between the quality of solution and computational time.

Traversing capacity of the algorithm

The information structure of the intelligent optimization algorithm is corrected dynamically according to the search behavior in practice. The intelligent optimization algorithm needs to keep the diversity of samples. It is even better to reach each solution in the sense of probability. This capacity of the algorithm is called the traversing capacity. The sample diversity can be reflected by the generation of the same sample probability in the intelligent algorithm as in Equation (19).

\[ \omega = \frac{X_{d=0}}{C_N} \times 100\% \]  

(19)

where \( d \) is the Euclidean distance. If \( d = 0 \), it explains why the two samples are the same. \( X_{d=0} \) means the number of samples with the Euclidean distance as 0 in generations of samples. \( N \) is the total amount of samples of each generation, which should be 50. The effectiveness of those algorithms is rooted in the general principle that ‘nature always finds the best way’ from the last generation. When the algorithm evolves, samples get closer to the objective. If the whole pattern of evolution changes just too fast, there will be more same samples in the same generation. Therefore the higher probability of the same samples may result in stopping of algorithms. The sample diversities of each generation of GA, PSO and CSO are shown in Figure 7. The horizontal axis is generation. The vertical axis stands for the probability of the same samples. The probability of the same samples of genetic algorithm is 2%. The samples of each generation for the particle swarm algorithm show diversity. After the second generation, \( \omega = 0 \) as shown in Figure 7(b), which illustrates that no identical samples exist. However, as shown in Figure 7(c), the probability of the same samples of each generation of the cat swarm algorithm exhibit a multi-peak curve illustrating that the cat swarm algorithm constantly keeps the sample diversity to avoid swamping into the local optimum.

Algorithm offset ability

Obviously, the intelligent optimization algorithm is not a simple random searching algorithm. It furthers the next search specifically, which can accelerate the search process by reducing the search blindness. Thus it is an algorithm with self-adaptability. This stressed searching ability of the intelligent optimization algorithm is called offset ability.

The mean value of samples can be used to represent the offset ability of the intelligent optimization algorithm:

\[ E(f(S))/E(f(U)) > 1 \]  

(20)

where \( S \) is the random variable of the intelligent optimization algorithm, \( U \) is the random variable of the feasible solutions.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Number of CATS/Particles 20</th>
<th>Number of CATS/Particles 40</th>
<th>Number of CATS/Particles 50</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>30</td>
<td>43</td>
<td>56</td>
</tr>
<tr>
<td>PSO</td>
<td>34</td>
<td>45</td>
<td>58</td>
</tr>
<tr>
<td>CSO</td>
<td>37</td>
<td>46</td>
<td>67</td>
</tr>
</tbody>
</table>

Table 3 | The computation time in seconds with different population size

Figure 7 | Traversal capacity of GA, PSO and CSO.
solution. This study chooses value 2 as the step size. The mean value of the offset ability of each generation for the genetic algorithm is 1.2; particle swarm algorithm mean value is 0.988, which is smaller than that for the cat swarm algorithm mean value 1.48.

Algorithm convergence ability

The convergence of the particle swarm algorithm and cat swarm algorithm is showed in Figure 8. The horizontal axis represents the generation and the vertical axis represents the objective function. The genetic algorithm shows the optimal solution in the 29th generation. The particle swarm algorithm presents the optimal solution in the 36th generation and the cat swarm algorithm presents the optimal solution in the 13th generation. Combining with the optimization results, we can see that the cat swarm algorithm is the fastest in the optimization process and it is the least prone to the local optimum.

CONCLUSION

In this research paper, a new model is developed to handle the optimization of channel trapezoidal section which is based on the side wall stability calculation and frost heave resistance. This study clearly demonstrates the capability of CSO in solving the complexity, non-lined and multi-objective channel design problems. The optimal parameters of the cross-section are more scientific and reasonable. It not only guarantees the stability and frost heave resistance of the cross-section, but also minimizes the lining cost and the land acquisition cost. The results show that the cat swarm optimization is compares very well with the genetic algorithm and particle swarm algorithm. A main channel of the Qinghe Irrigation Area of Farm 853 in Heilongjiang Province is taken as an example. The computed results show that 8.2% and 10.8% construction investment can be saved as compared with the genetic algorithm and particle swarm algorithm respectively. Besides, both the offset ability, the traversal capacity and convergence ability of the cat swarm algorithm are superior to those of the genetic algorithm and particle swarm algorithm except for computational time. Thus in general the CSO is a potential candidate for optimization of channel cross-section.

ACKNOWLEDGEMENTS

This study is supported by the National Natural Science Foundation of China (No. 41071053), the Sub-Task of the National Science and Technology Support Program for Rural Development in the 12th Five-Year Plan of China (No. 2013BAD20B04-S3), the Specialized Research Fund for the Public Welfare Industry of the Ministry of Water Resources (No. 201301096), the Specialized Research Fund for Innovative Talents of Harbin (Excellent Academic Leader) (No. 2013RFXXJ001), the Science and Technology Research Program of the Education Department of Heilongjiang Province (No. 12531012), the Science and Technology Program of Water Conservancy of Heilongjiang Province (No. 201319) and the Northeast Agricultural University Innovation Foundation for Postgraduates (No. yjscx14069).

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First received 11 April 2015; accepted in revised form 14 August 2015. Available online 24 August 2015