Journal of Corrosion and Materials
www.corromat.com

J. Corros. Mater. **48** (2023) 58–64
https://doi.org/10.61336/jcm2023-6

Urban and Rural Multi-Objective Programming Based on Augmented Lagrange Multiplier Method for Nonlinear Mathematical Equations

Yan Zeng[1,*]

[1] *Jiangxi Normal University, Nanchang 330022, China*

(Received: 2 January 2023. Received in revised form: 23 October 2023. Accepted: 2 November 2023. Published online: 5 November 2023.)

Abstract

Augmented Lagrange multiplier method is an important method to solve constrained optimization problems. In recent years, it has become more important to study the application of augmented Lagrange multiplier method. This paper first introduces the augmented Lagrange multiplier method, which leads to the development of the application of the augmented Lagrange method to nonlinear mathematical equations, and summarizes the augmented Lagrange multiplier. The application of nonlinear mathematical equations. At the same time, the paper specifies the application of the augmented Lagrange method in urban and rural multi-objective programming, and proves the practical application of the augmented Lagrange multiplier nonlinear mathematical equations.

Keywords: Augmented Lagrange multiplier method, Town and Country Planning, multi-objective programming, nonlinear mathematical equations.

1. Introduction

When solving the optimization problem with constraints, there is an important method to transform the constraint optimization problem into an unconstrained optimization problem by a suitable method. In the topic of seeking the best solution, the Lagrange multiplier method, named after the famous American scholar Joseph, is a method to explore the extremum of ternary functions. There are several conditions that restrict the variables of such functions. Its main solution is to convert a problem with the optimal solution of n variables and k constraints into an extremum problem of a system of equations with $n+k$ variables. The variables here have a feature, no Any constraint is called an unconstrained variable. This method introduces a scalar unknown that has not been passed, that is, the Lagrange function parameter [1].

Among the problems encountered, the augmented Lagrange multiplier method is regarded as an important method to solve the constrained optimization problem. In recent years, it has been applied in many important scientific fields such as engineering, national defence, economics, finance and social sciences [2]. For example, the horizontal well perforation optimization design problem based on the Lagrange multiplier method is to first adopt the augmented Lagrange multiplier method, and then combine the reservoir seepage model to consider the horizontal well bottom flow pressure. Or, in the case of constant production, the maximum production and minimum downhole flow pressure are required for research, and the logarithmic diversion is optimized for the perforation density of horizontal wells. The application of the augmented Lagrange multiplier method involves many aspects. Therefore, the study of the application of the augmented Lagrange multiplier method has great significance.

2. Augmented Lagrange Multiplier Method

2.1 Constrained nonlinear programming

Solving the usual problem of not linear programming is much more troublesome than unconstrained and linear programming problems. Now, we consider a simple example illustrate this fact. Consider the problem [3]

$$\begin{cases} \min \quad f(x) = x_1^2 + x_2^2, \\ s.t. \quad x_1 + x_2 - 1 \geq 0, \\ \qquad 1 - x_1 \geq 0, \\ \qquad 1 - x_2 \geq 0, \end{cases} \tag{1}$$

The above example 1 shows that for nonlinear programming problems, even if the constraints are linear, the optimal solution is not necessarily at the vertices and this brings difficulties to solving them. On the other hand, due to the existence

*Corresponding author (zengyan98@sina.com)

of the constraint, if there is no constraint, starting from any initial point $x^{(0)}$ and performing a one-dimensional search along the negative gradient direction of $f(x)$, the unconstrained minimum point $(0,0)^T$ of the objective function is obtained. However, with constraints, in order to make the one-dimensional search and obtain a feasible point, the step size must be limited, so that we can only go to a point on the boundary, when $x^{(0)}$ is taken. When it is not on line $x_1 - x_2 = 0$, the point $x^{(1)}$ will not be the optimal solution $x*$. Therefore, it is necessary to continue iterating to find a feasible point that has not been seen, so that the objective function has a smaller value. However, a feasible point has not been found along the negative gradient direction of $f(x)$ at $x^{(1)}$, so the gradient iteration can no longer proceed, although it may be far from the optimal solution. This is the essential difference between constrained nonlinear programming and unconstrained nonlinear programming, and it is also the fundamental problem of solving constraint problems. In order to overcome such difficulties, in other words, when the existing points are on the edge of the area, in order to continue the iteration, not only the demand search direction has the possibility of lowering the objective function. There are also requirements to be feasible in this direction. For example, there is a small line segment that is entirely contained within the feasible domain, and a direction like this is called a feasible direction. Therefore, in the design of the iterative method for solving constrained nonlinear programming, a falling feasible direction $d^{(k)}$ should be constructed at each iteration point $x^{(k)}$.

Another way to solve constrained nonlinear programming is to replace the original problem with its simple solution as a new approximate solution to the original problem with a simpler problem with a better solution. For example, the nonlinear function in the objective function and the constraint is replaced by their first-order Taylor polynomial or second-order Taylor polynomial approximation, or by an unconstrained nonlinear programming approximation.

2.2 Penalty function outer point method

There is a class of penalty function methods that perform outside the feasibility area. It can also be called the outer point method. It adds a matching penalty to the objective function for the iteration point that does not obey the constraint, but does not target the feasible point. The iteration point of this method is often moved outside the feasible domain. Consider general constraint optimization problems

$$\begin{cases} \min \quad f(x) \\ s.t. \quad g_i(x) \geq 0, \ i = 1, \cdots, m, \\ \quad h_j(x) = 0, \ j = 1, \cdots, l. \end{cases} \tag{2}$$

Define helper functions as:

$$F(x, \sigma) = f(x) + \sigma P(x). \tag{3}$$

Here $P(x)$ can take the form

$$P(x) = \sum_{i=1}^{m} [\max\{0, -g_i(x)\}]^{\alpha} + \sum_{j=1}^{l} |h_j(x)|^{\beta} \tag{4}$$

where $\alpha, \beta \geq 1$ is a constant, usually $\alpha = \beta = 2$.

In this way, it turns into an unconstrained problem

$$\min \quad F(x, \sigma) \overset{def}{=} f(x) + \sigma P(x) \tag{5}$$

where σ is a large positive number [4].

Generally speaking, we call $\sigma P(x)$ a penalty, σ a penalty factor and $F(x, \sigma)$ is called a penalty function.

Case 1: Considering the nonlinear programming

Define the penalty function as:

$$\begin{aligned} F(x,\sigma) &= (x_1 - 1)^2 + x_2^2 + \sigma[\max\{0, -(x_2 - 1)\}]^2 \\ &= \begin{cases} (x_1 - 1)^2 + x_2^2, & \text{when } x_2 \geq 1, \\ (x_1 - 1)^2 + x_2^2 + \sigma(x_2 - 1)^2, & \text{when } x_2 < 1, \end{cases} \end{aligned} \tag{6}$$

Solving $\min F(x, \sigma)$ with analytical method, there is

$$\begin{aligned} \frac{\partial F}{\partial x_1} &= 2(x_1 - 1), \\ \frac{\partial F}{\partial x_2} &= \begin{cases} 2x_2, \text{when } x_2 \geq 1, \\ 2x_2 + 2\sigma(x_2 - 1), \text{when } x_2 < 1, \end{cases} \end{aligned} \tag{7}$$

Taking $\frac{\partial F}{\partial x_1} = 0, \quad \frac{\partial F}{\partial x_2} = 0$, we get

$$x_\sigma^* = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 \\ \frac{\sigma}{1+\sigma} \end{bmatrix} \tag{8}$$

When $\sigma \to +\infty$, it is easy to see that

$$x_\sigma^* \to x^* = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \tag{9}$$

$x*$ happens to be the optimal solution for the nonlinear programming. The optimal solution without the constraint problem obtained by the above described method will not satisfy the constraint in the normal case. This solution will live outside the feasible domain. When σ increases, it gets closer to $x*$, so this method is called the external point method. In the actual calculation process, it is very necessary to consider how to choose the penalty factor σ. When we encounter this kind of situation, our way is to take a positive series $\{\sigma_k\}$ that is close to infinity and strictly increasing.

$$\min f(x) + \sigma_k P(x) \tag{10}$$

2.3 Lagrange multiplier method

If f, g_i, h_j are differentiable then for question (11), a Lagrange function can be established:

Kuhn-Tucher condition [5] for nonlinear programming (11) is: if f, g_i, h_j are differentiable and

$$\nabla g_i(x^*), \quad i \in I(x^*), \nabla h_j(x^*), \quad j = 1, \cdots, l$$

are linearly independent then the necessary condition for $\nabla g_i(x^*), i \in I(x^*), \nabla h_j(x^*), j = 1, \cdots, l$ to be the optimal solution of (11) is that there are corresponding Lagrange multipliers λ^* and μ^* where $I(x^*) = \{i | g_i(x^*) = 0\}$ is called the set of effective constraint indicators for x^*. The feasible point that satisfies the K-T condition becomes the K-T point and ate the most advantageous point.

Case 2: Consider the following nonlinear programming and finding its K-T point, such that

$$\begin{cases} \min f(x) = x_1^2 + x_2 \\ g_1(x) = -x_1^2 - x_2^2 + 9 \geq 0 \\ g_2(x) = -x_1 - x_2 + 1 \geq 0 \end{cases} \tag{11}$$

Solution: The K-T condition for nonlinear programming is here

$$\begin{bmatrix} 2x_1 \\ 1 \end{bmatrix} - \lambda_1 \begin{bmatrix} -2x_1 \\ -2x_2 \end{bmatrix} - \lambda_2 \begin{bmatrix} -1 \\ -1 \end{bmatrix} = 0 \tag{12}$$

$$\lambda_1(-x_1^2 - x_2^2 + 9) = 0 \tag{13}$$

$$\lambda_2(-x_1 - x_2 + 1) = 0 \tag{14}$$

$$\lambda_1 \geq 0, \lambda_2 \geq 0 \tag{15}$$

Coupled with constraints

$$\begin{matrix} -x_1^2 - x_2^2 + 9 \geq 0 \\ -x_1 - x_2 + 1 \geq 0 \end{matrix} \tag{16}$$

(1) If the (14) equation is not true, then (15) has $\lambda_1 = 0$, and then (13) gives $\lambda_2 = -1$, which contradicts (16). Therefore, the (15) equation equal sign must be established.

(2) If the (17) equation is not true, then (16) has $\lambda_2 = 0$ and substitutes (2.2)

$$x_1(1 + \lambda_1) = 0, \quad 1 + 2\lambda_1 x_2 = 0, \tag{17}$$

From the first formula in $\lambda_1 \geq 0$ and (18), we get $x_1 = 0$. Substituting the second formula of (16) (the equal sign is established) and the contact (18), and $\lambda_1 = \frac{1}{6}, x_2 = -3$ is obtained.

(1) If the equation (17) is equal, there are two equations (16) and (17) to solve two points $x = \left(\frac{1+\sqrt{17}}{2}, \frac{1-\sqrt{17}}{2}\right)^T$ and $\left(\frac{1-\sqrt{17}}{2}, \frac{1+\sqrt{17}}{2}\right)^T$.

Note that the formula (15), from the first line equation in (12), knows that x_1 cannot take $\frac{1+\sqrt{17}}{2}$, and if $\frac{1-\sqrt{17}}{2}$ is taken, then $x_2$should take $\frac{1+\sqrt{17}}{2}$, which makes the second line equation in (12) impossible. . Therefore, there is a unique K-T point for the nonlinear programming sought.

2.4 Augmented Lagrange Multiplier Method

The augmented Lagrange multiplier method is a way of connecting the penalty function outer point method based on the Lagrange multiplier method. Its basic idea is to put the Lagrange multiplier into punishment. In the function, to establish an augmented Lagrange function, the search for the optimal solution in the process, through the constant penalty factor and Lagrange adjustment of the multiplier, in order to get the effect of Lagrange is different Based on the lowest point Lagrange function for solving the unconstrained minimum optimization and the limit of the original objective function near the extreme point of the Lagrange function, a convergence criterion close to the optimal solution is obtained [6]. Considering the problem (A), an augmented Lagrange function can be constructed

$$\begin{aligned} F(x,\lambda,\mu,\sigma) = f(x) + \frac{1}{2\sigma}\sum_{i=1}^{m}\left\{[\max(0,\lambda_i - \sigma g_i(x))]^2 - {\lambda_i}^2\right\} \\ - \sum_{j=1}^{l}\mu_j h_j(x) + \frac{\sigma}{2}\sum_{j=1}^{l} h_j^2(x). \end{aligned} \tag{18}$$

2.4.1 Consider a nonlinear optimization problem with only equality constraints

$$\begin{cases} \min f(x) \\ h_i(x) = 0 \quad i = 1, \cdots, m \end{cases} \tag{19}$$

Then the Lagrange function of the optimization problem is

$$F(x,\lambda,c) = f(x) + \sum_{i=1}^{m}\lambda_i h_i(x) + \frac{c}{2}\sum_{i=1}^{m}[H_i(x)]^2 \tag{20}$$

Among them, c is a positive penalty coefficient.

The basic idea of the augmented Lagrange function method is to gradually approach the solution of the optimization problem (19) by solving the rotation of the unconstrained optimal problem (20) given by the given value and adjusting the values of λ and c. Therefore, the solution to the constrained optimization problem can be solved as an unconstrained optimization problem. In this way, this method has the advantages of the Lagrange function method and the penalty function method on the one hand, and on the other hand, it overcomes the disadvantages of their existence, and is called a more useful solution to the nonlinearity. A method of constraining optimization problems.

Example 2.1 (Solving problems with the multiplier method)**.** *Consider the following problem:*

$$\begin{cases} min \quad 2x_1^2 + x_2^2 - 2x_1x_2, \\ s.t. \quad h(x) = x_1 + x_2 - 1 = 0. \end{cases} \tag{21}$$

Consider

$$\phi(x,\mu,\sigma) = 2x_1^2 + x_2^2 - 2x_1x_2 - \mu(x_1 + x_2 - 1)^2 \tag{22}$$

Take $\sigma = 2$, $\mu^{(1)} = 1$, and solve $min\,\phi(x,1,2)$ by analytical method, and the minimum point is

$$x(1) = \begin{bmatrix} x_1^{(1)} \\ x_2^{(1)} \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ \frac{3}{4} \end{bmatrix} \tag{23}$$

Fix μ has $\mu(2) = \mu(1) - \sigma h(x(1)) = 1 - 2\cdot\frac{1}{4} = \frac{1}{2}$. Then solve $min\,\phi\left(x,\frac{1}{2},2\right)$ again, get $x^{(2)}$, and continue like this. In general, at the kth iteration, the minimum point of $\phi(x,\mu^{(k)},2)$ is

$$x^{(k)} = \begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \end{bmatrix} = \begin{bmatrix} \frac{1}{6}(\mu^{(k)} + 2) \\ \frac{1}{4}(\mu^{(k)} + 2) \end{bmatrix} \tag{24}$$

$$\mu^{(k+1)} = \frac{1}{6}\mu^{(k)} + \frac{1}{3} \tag{25}$$

It is easy to see that at time $k \to +\infty$, $\mu^{(k)} \to \frac{2}{5}$, $x^{(k)} \to \left(\frac{2}{5},\frac{3}{5}\right)^T$, respectively, the optimal nonlinear programming, the optimal multiplier and the optimal solution are calculated.

2.4.2 Considering inequality constraints

First consider the problem with only inequality constraints

$$\begin{cases} \min & f(x) \\ s.t. & g_i(x) \geq 0, \end{cases}$$

$i = 1, 2, \cdots, m$. Using the result of the equality constraint, introduce the variable y_i and convert the above into the equality constraint problem

$$\begin{cases} \min & f(x) \\ s.t. & g_i(x) - y_i^2 \geq 0, \end{cases}$$

$i = 1, 2, \cdots, m$. Thus, the augmented Lagrange function can be defined:

$$\begin{aligned} &\widetilde{\varphi}(x, y, \mu, \sigma) \\ &= f(x) - \sum_{i=1}^{m} \mu_i (g_i(x) - y_i^2) + \frac{\sigma}{2} \sum_{i=1}^{m} \left(gi(x) - y_i^2\right)^2 \end{aligned} \tag{26}$$

Thus turning the problem into solving min $\widetilde{\phi}(x, y, \mu, \sigma)$,, to rewrite the form of $\widetilde{\phi}$ to

$$\begin{aligned} &\widetilde{\varphi}(x, y, \mu, \sigma) \\ &= f(x) + \sum_{i=1}^{m} \left\{ \frac{\sigma}{2} \left[y_i^2 - \frac{1}{\sigma} (\sigma g_i(x) - \mu_i) \right]^2 - \frac{\mu_i^2}{2\sigma} \right\} \end{aligned} \tag{27}$$

In the form of $\widetilde{\phi}$, it can be seen that for $\widetilde{\phi}$ to be extremely small, the value of y_i^2 must be $y_i^2 = \frac{1}{\sigma} \left[\max\left\{0, \sigma g_i(x) - \mu_i\right\}\right]^2$. Thus, the above formula can be substituted for $\widetilde{\phi}$ to eliminate y_i, thus defining an augmented Lagrange function.

$$\widetilde{\varphi}(x, \mu, \sigma) = f(x) + \frac{1}{2\sigma} \sum_{i=1}^{m} \left\{ \left[\max(0, \mu_i - \sigma g_i(x))\right]^2 - \mu_i^2 \right\} \tag{28}$$

To sum up, the inequality constraint problem can be changed to the unconstrained problem min $\widetilde{\varphi}(x, \mu, \sigma)$.

2.5 Calculation of augmented Lagrange multiplier method

First definition of semi-smooth function [7]: Let $G : \Re^n \to \Re^m$, be a partial Lipschitz continuous map. We call it G in $x \in \Re^n$ is semi-smooth, when

(i) G is directional at x;

(ii) for any of $\Delta x \in \Re^n$ and $H \in \partial G(x + \Delta x)$, and $\Delta x \to 0$

$$G(x + \Delta x) - G(x) - H(\Delta x) = (\|\Delta x\|) \tag{29}$$

Further, G is said to be strongly semi-smooth at $x \in \Re^n$, if G is semi-smooth at x, and for any $\Delta x \in \Re^n$ and $H \in \partial G(x + \Delta x)$ $\Delta x \to 0$, there is

$$\|x - \hat{x}\| = \min\left\{\|x - y\| : y \in C\right\} \tag{30}$$

Let $\hat{x}$ be the projection of x on set C, denoted $\prod_C(x)$. Therefore, the projection operator $\prod_C : \Re^n \to C$ is defined for each $x \in \Re^n$ and is non-expanded. Algorithm: Select the initial point $x^1 \in \Omega, u^k \in \Re_+^m$ of the original problem, then the $k+1$ point iteration point x^{k+1}, u^{k+1} is calculated by:

$$\begin{aligned} x^{k+1} \in \arg\min \left\{ \tfrac{1}{2} \|y - x^k\|^2 + \sigma F(x^{k+1}, y, u^k) \middle| y \in \Omega \right\}, \\ u^{k+1} = \textstyle\prod_+ (u^k + \sigma g(x^{k+1})) \end{aligned} \tag{31}$$

3. Augmented Lagrange function optimization method for urban and rural planning

3.1 The establishment of urban and rural planning model

Urban and rural planning has always been an important goal in the urban and rural management category [8]. According to its special characteristics of urban and rural margins, in the urban and rural planning, the total variation minimization model has obvious priority [9]. The urban and rural planning model is expressed as:

$$y = Ax + n \tag{32}$$

Among them, y is degenerate urban and rural, n is noise [10] (this kind of noise is generally Gaussian white noise or salt and pepper noise, only Gaussian white noise is considered), A is a linear degradation operator (generally written in convolution form) x is the original urban and rural area to be restored.

The urban-rural restoration is caused by the degraded urban and rural y and the operator A to restore the high degree of urban and rural x at the beginning. Urban and rural restoration models often have reliability and regularization terms:

$$\min_{x} \quad f(x) = \lambda\varphi(x) + \|Ax - y\|_F^2 \tag{33}$$

Where $\varphi(x)$ is a regular term and $\lambda > 0$ is a regularization parameter. The all-variation model suppresses urban-rural noise [11], so it is widely used in urban and rural recovery. Given a two-dimensional gravy-scale urban-rural x of $m \times n$, its discrete total variational model can be defined as:

$$TV(x) = \|(D_h x, D_v x)\| \tag{34}$$

According to the norm of the matrix used, it is possible to distinguish the isotropic and anisotropic total variation TV more strongly.

$$\begin{aligned} TV_{iso}(x) &= \|(D_h x, D_v x)\|_{iT} \\ &= \sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{(D_h x)_{i,j}^2 + (D_v x)_{i,j}^2} \end{aligned} \tag{35}$$

$$\begin{aligned} TV_{aniso}(x) &= \|(D_h x, D_v x)\|_{aT} \\ &= \|D_h x\|_{l_1} + \|D_v x\|_{l_1} \end{aligned} \tag{36}$$

Here, the former D_h and D_v refer to the horizontal direction, the latter refers to the gradient operator in the vertical direction, and the matrix l_1 norm adds the absolute values of the all elements. The all-variation urban-rural planning model is:

$$\underset{x}{argmin} f(x) = \lambda TV(x) + \frac{1}{2}\|Ax - y\|_F^2 \tag{37}$$

About the issue of urban and rural recovery, isotropic TV usually achieves better recovery. Therefore, we consider the algorithm of the recovery model for the general variation of the isotropic nature of urban and rural areas.

3.2 Augmented Lagrange Function Algorithm for Urban and Rural Planning Problems

Substituting the auxiliary variable u for x in TV, the equivalent of (39) becomes the solution to the equality constraint problem:

$$\begin{cases} \underset{x,u}{\text{argmin}} \lambda TV(u) + \frac{1}{2}\|Ax - y\|_F^2 \\ \qquad s.t. \quad u = x \end{cases} \tag{38}$$

Substituting isotropic TV into (39) gives you:

$$\underset{x}{argmin} f(x) = \lambda\| \,(D_h x, D_v x)\, \|_{iT} + \frac{1}{2}\|Ax - y\|_F^2 \tag{39}$$

Adding the auxiliary variables $u$and v, (41) can become the following equation constraint optimization problem:

$$\begin{cases} \underset{u,v,x}{\text{argmin}} \lambda\| \,(u, v)\, \|_2 + \frac{1}{2}\|Ax - y\|_F^2 \\ \quad s.t. \quad u = D_h x,\ v = D_v x \end{cases} \tag{40}$$

Through the transformation of the above various types, the original all-variation urban-rural planning problem is transformed into an equivalent equation-constrained optimization problem, and further, the augmented Lagrange algorithm can be used to efficiently solve the above-mentioned equality constraint problem. Solve. The augmented Lagrange function corresponding to (40) is:

$$\begin{aligned} &L(x, u, \kappa, \delta) \\ &= \lambda TV(u) + \frac{1}{2}\|Ax - y\|_F^2 + \kappa^T(u - x) + \frac{\delta}{2}\|Ax - y\|_F^2 \end{aligned} \tag{41}$$

Where κ is the Lagrange multiplier and $\sigma \geq 0$ is the penalty parameter.

The augmented Lagrange method has the advantages of unconditional convergence, which makes it have unique advantages in urban and rural planning problems.

The objective function (43) can be modified to obtain a modified augmented Lagrange objective function form:

$$L(x,u,p,\delta) = \lambda TV(u) + \frac{1}{2}\|Ax-y\|_F^2 + \frac{\delta}{2}\|u-x+p\|_F^2 \tag{42}$$

In order to make the solution easier, we use the inexact augmented Lagrange method to solve the problem by alternately updating the x and u strategies. Methods as below:

$$x_{k+1} = (A^H A + \delta_k)^{-1}(A^H y + \delta_k(u_k + p_k)) \tag{43}$$

$$u_{k+1} = \text{argmin}_u \lambda/\delta_k TV_{iso}(u) + \frac{1}{2}\|u-(x_{k+1}-p_k)\|_F^2 \tag{44}$$

$$p_{k+1} = p_k + u_{k+1} - x_{k+1}$$

$$\delta_{k+1} = p\delta_k$$

Where A^H represents the conjugate transpose of matrix A, $1 \le \rho \le 2$. If A is a convolution operator, you can use Fast Fourier Transform or Discrete Cosine Transform to calculate Ax and $A^H y$. Equation (46) is an urban-rural issue. Theoretical analysis shows that when $\delta_\infty < \delta_{\max}$, the convergence and the optimality of the solution can be verified. If you take $\rho = 1$, you can get the alternate direction multiplier method. Many urban and rural reduction algorithms based on augmented Lagrange are solved using the alternating direction multiplier method.

4. Conclusion

The augmented Lagrange multiplier method is used as a solution to the constraints and then the best solution for engineering, defence, economics, finance and social sciences. Therefore, it is of great significance to explore the augmented Lagrange multiplier method. By explaining the generation and development of the augmented Lagrange multiplier method, augmented Lagrange multiplier method is better applied. Among them, the augmented Lagrange multiplier method is a combination of the penalty function outer point method and the Lagrange multiplier method, and the solution accuracy is high, which is a very practical design optimization method. This paper illustrates the augmented Lagrange penalty in the application process through the practical application example. Firstly, the mathematical model is established for the actual problem. Then the method can speed up the process of finding the optimal result and make the optimal result more accurate.

References

[1] Griva, Igor, Polyak, & Roman, A. Proximal point nonlinear rescaling method for convex optimization. Numerical Algebra Control & Optimization, (2),1(2017), 283-299.

[2] Cheng, D., Yang, J., Wang, J., Shi, D., & Liu, X. Double-noise-dual-problem approach to the augmented lagrange multiplier method for robust principal component analysis. Soft Computing, (10),21(2017), 2723-2732.

[3] Gatica, G. N., Munar, M., & Sequeira, F. A. A mixed virtual element method for the navier–stokes equations. Mathematical Models and Methods in Applied Sciences, (14),28 (2018), 2719-2762.

[4] Lin, H., Wang, L., Yu, J., Teng, Z., & Dai, H. Nonlinear error compensation for load cells based on the optimal neural network with an augmented lagrange multiplier. IEEE Transactions on Instrumentation & Measurement, (11),64 (2015), 2850-2862.

[5] Chao, K., & Wen, S. Augmented lagrangian duality for composite optimization problems. Journal of Optimization Theory & Applications, (3), 165(2015), 763-784.

[6] Chen, H., Qiu, W., Ke, S., & Solano, M. A superconvergent hdg method for the maxwell equations. Journal of Scientific Computing, (3),70(2017), 1-20.

[7] Huang, W., & Wang, Y. Discrete maximum principle for the weak galerkin method for anisotropic diffusion problems. Communications in Computational Physics, (1),18 (2015), 65-90.

[8] Murea, C. M., & Hentschel, H. G. A finite element method for growth in biological development. Mathematical Biosciences & Engineering Mbe, (2),4 (2017),339-353.

[9] Khalid, M., Sultana, M., Arshad, U., & Shoaib, M. A comparison between new iterative solutions of non-linear oscillator equation. International Journal of Computer Applications, (4),128(2015), 1-5.

[10] Jie, M. A., Zhang, X. M., & Yuan, H. C. Character rectification method based on augmented lagrange multiplier using parallel splitting. Journal of Optoelectronics•laser, (6),26(2015), 1170-1178.

[11] Armand, P., & Omheni, R. A mixed logarithmic barrier-augmented lagrangian method for nonlinear optimization. Journal of Optimization Theory & Applications, (2),173 (2017),1-25.