

# A REVIEW OF A CERTAIN PROBLEMS IN OPTIMIZATION

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## ABSTRACT

*In mathematics and computer science, an **optimization problem** is the problem of finding the best solution from all feasible solutions. Optimization problems can be divided into two categories depending on whether the variables are continuous or discrete. An optimization problem with discrete variables is known as a combinatorial optimization problem. The aims and objectives of this paper work, is to basically study certain problems in optimization of scalar value and vector valued function, general cases, some related theorems and their proofs.*

## I. INTRODUCTION

The basic elements of optimization can be found in the calculus courses where maximum and minimum (extremum) problems are concerned with those values of the independent variables for which a given function attains its maximum or minimum value. A result of the celebrated mathematician Pierre de Fermat states that if a differentiable real-valued function of one variable has a maximum or minimum at a point, then its derivative is zero at that point. Moreover, optimization deals with determining the best (optimal) solutions to mathematical problems representing an important occurring in various domains, such as engineering, economics, biotechnology, military science and medical science. The origin of this topic can be traced to the following classical results of Weierstrass and Euler respectively: 'every-real valued continuous function defined on a closed and bounded interval of a real numbers attain its minimum and maximum' on that interval, and 'the shortest path joining origin to a point in the plane is a straight line'. However, the importance of this topic has been realized only after 1950 and most of the results in this area has been discovered in the last four decades.

Moreover, the act of achieving the best possible result under given circumstances in design, construction, maintenance, engineers have to take decisions. The goal of all such decisions is either to minimize cost or to maximize benefit. The cost or the benefit can be usually expressed as a function of certain design variables. Hence, optimization is the process of finding the conditions that give the maximum or the minimum value of a function. It is obvious that if a point  $x_1$  corresponds to the minimum value of a function  $f(x)$ , the same point corresponds to the maximum value of the function  $f(x)$ . Thus, optimization can be taken to be minimization. There is no single method available for solving all optimization problems efficiently. Hence, a number of methods have been developed for solving different types of problems. Optimum seeking methods are also known as mathematical programming techniques, which are a branch of operations research. Operations research is coarsely composed of the following areas. Mathematical programming methods. These are useful in finding the minimum of a function of several variables under a prescribed set of constraints. Stochastic process techniques.

These are used to analyze problems which are described by a set of random variables of known distribution. Statistical methods. These are used in the analysis of experimental data and in the construction of empirical models. However, readers may find detailed accounts of non-smooth optimization problems in [Cl 83, ClWo 98, HiLa 93, Mi 11aNe 92, OuKo 98, Ro 81]. Current developments concerning algorithmic optimization and related software may be seen in [CoGo 2000, GoTo 2000, Ke 95, MoWr 93, Po 97, Po 87].

## II. MATERIAL AND METHODOLOGY

Let  $X$  be a normed space,  $K$  a nonempty subset of  $X$  and  $F : K \rightarrow \mathbb{R}$  a function on  $K$  into  $\mathbb{R}$ . The general optimization problem  $(P)$  is to find an element  $u \in K$  such that  $F(u) \leq F(v)$ ,  $\forall v \in K$ . If such an element exists, we say that  $u$  minimizes  $F$  on  $K$ , and write

$$F(u) = \inf_{v \in K} F(v)$$

such a solution is called global minimum.

And in this situation, we say that  $f$  has a minimum at  $u$ . If  $K = X$ , this problem is referred to as the unconstrained optimization problem, while the case  $K \subsetneq X$  is called the constrained optimization problem.

**Definition 3.1** Let  $A$  be a subset of a normed space  $X$  and  $f$  a real-valued function on  $A$ .  $f$  is said to have a local or relative minimum (maximum) at a point  $x_0 \in A$  if there is an open sphere  $S_r(x_0)$  of  $S$  such that  $f(x_0) \leq f(x)$  ( $f(x) \leq f(x_0)$ ) holds for all  $x \in S_r(x_0) \cap A$ . If  $f$  has either a relative minimum or relative maximum at  $x_0$ , then  $f$  is said to have a relative extremum. The set  $A$  on which an extremum problem is defined is often called the admissible set.

**Theorem 3.1** Let  $f : X \rightarrow \mathbb{R}$  be a Gateaux differentiable functional at  $x_0 \in X$  and  $f$  have a local extremum at  $x_0$ , then  $Df(x_0)t = 0$  for all  $t \in X$ .

**Proof** For every  $t \in X$ , the function  $f(x_0 + t)$  (of the real variable  $t$ ) has a local extremum at  $t = 0$ . Since it is differentiable at 0, it follows from ordinary calculus that

$$\frac{d}{dt} f(x_0 + t) \Big|_{t=0} = 0$$

This means that  $Df(x_0)t = 0$  for all  $t \in X$ , which proves the theorem.

**Remark 3.1**

(i) It follows immediately from Theorem 6.1 that if a functional  $f : X \rightarrow \mathbb{R}$  is Frchet differentiable at  $x_0 \in X$  and has a relative extremum at  $x_0$ , then  $dT(x_0) = 0$ .

(ii) Let  $f$  be a real-valued functional on a normed space  $X$  and  $x_0$  a solution of  $(P)$  on a convex set  $K$ . If  $f$  is a Gateaux differentiable at  $x_0$ , then

$$Df(x_0)(x - x_0) > 0 \text{ or } \leq 0 \text{ for all } x \in K.$$

**Verification** Since  $K$  is a convex set,  $x_0 + t(x - x_0) \in K$  for all  $t \in (0,1)$  and  $x \in K$ . Hence

$$f(x_0 + t(x - x_0)) - f(x_0) = Df(x_0)t(x - x_0) + o(\|t(x - x_0)\|) > 0.$$

**Theorem 3.2** Let  $K$  be a convex subset of a normed space  $X$ .

1. If  $J : K \rightarrow \mathbb{R}$  is a convex function, then  $(P)$  has a solution  $u$  whenever  $J$  has a local minimum at  $u$ .

2. If  $J : X \rightarrow \mathbb{R}$  is a convex function defined over an open subset of  $X$  containing  $K$  and  $J$  is Frchet differentiable at a point  $u \in K$ , then  $J$  has a minimum at  $u$  ( $u$  is a solution of (P)) if and only if

$$J'(u)(v - u) \geq 0 \text{ for every } v \in K$$

If  $K$  is open, then (3.1) is equivalent to

$$J'(u) = 0 \text{ (often called Eulers equation)}$$

Proof 1. Let  $v = u + w$  be any element of  $K$ . By the convexity of  $J$   $J(u + w) \leq (1 - \theta)J(u) + \theta J(v)$ ;  $\theta \in [0, 1]$  which can also be written as

$$J(u + w) - J(u) \leq \theta (J(v) - J(u)); \theta \in [0, 1]$$

Since  $J$  has a local minimum at  $u$ , there exists  $\delta > 0$  such that  $J(u + \theta w) \geq J(u)$ , which implies that  $J(v) \geq J(u)$ .

2. By Remark 3.1(ii), the necessity of (3.1) equation holds even without convexity assumption on  $J$ . For the sufficiency part, we observe that

$$J(v) - J(u) \geq J'(u)(v - u) \text{ for every } v \in K$$

Since  $J$  is convex

$$J(\theta u + (1 - \theta)v) \leq \theta J(u) + (1 - \theta)J(v) \text{ for all } \theta \in [0, 1]$$

or

$$J(u + \theta(v - u)) \leq \theta J(v) + (1 - \theta)J(u)$$

$$J(v) - J(u) \geq \frac{J(u + \theta(v - u)) - J(u)}{\theta}$$

or

$$\frac{J(u + \theta(v - u)) - J(u)}{\theta} \geq J'(u)(v - u)$$

$$J(v) - J(u) \geq \lim_{\theta \rightarrow 0} \frac{J(u + \theta(v - u)) - J(u)}{\theta} = J'(u)(v - u) \geq 0$$

This proves that if  $J'(u)(v - u) \geq 0$ , then  $J$  has a minimum at  $u$ .

A functional  $J$  defined on a normed space is called coercive if  $\lim_{\|x\| \rightarrow \infty} J(x) = \infty$ .

Theorem (3.3) (Existence of Solution in  $\mathbb{R}^n$ ) Let  $K$  be a non-empty, closed convex subset of  $\mathbb{R}^n$  and  $J : \mathbb{R}^n \rightarrow \mathbb{R}$  a continuous function which is coercive if  $K$  is unbounded. Then there exists at least one solution of (P).

Proof Let  $u_k$  be a minimizing sequence of  $J$ ; that is, a sequence satisfying conditions  $u_k \in K$  for every integer  $k$  and  $\lim_{k \rightarrow \infty} J(u_k) = J(v)$ . This sequence is necessarily bounded, since the functional  $J$  is coercive, so that it is possible to find a subsequence  $u_{k_j}$  which converges to an element  $u \in K$  ( $K$  being closed). Since  $J$  is continuous,  $J(u) = \lim_{k \rightarrow \infty} J(u_{k_j}) = \inf_{v \in K} J(v)$  which proves the existence of a solution of (P).

Theorem 3.4 (Existence of Solution in Infinite-Dimensional Hilbert Space) Let  $K$  be a non-empty, convex, closed subset of a separable Hilbert space  $H$  and  $J : H \rightarrow \mathbb{R}$  a convex, continuous functional which is coercive if  $K$  is unbounded. Then (P) has at least one solution.

Proof As in the previous theorem,  $K$  must be bounded under the hypotheses of the theorem. Let  $u_k$  be a minimizing sequence in  $K$ . Then by Theorem  $u_k$  has a weakly convergent subsequence  $u_{k_j} \rightharpoonup u$ . By Corollary,  $J(u) = \liminf_{k \rightarrow \infty} J(u_{k_j})$ ;  $u_{k_j} \rightharpoonup u$  which, in turn, shows that  $u$  is a solution of (P). It only remains to show that the weak limit  $u$  of the sequence  $u_{k_j}$  belongs to the set  $K$ . For this, let  $P$  denote the projection operator associated with the closed, convex set  $K$ ; by another Theorem  $2 \langle Pu - u, w - Pu \rangle \leq 0$  for every integer

The weak convergence of the sequence  $w_n$  to the element  $u$  implies that

$$\lim_{n \rightarrow \infty} \int_K w_n u = \int_K u^2$$

Thus,  $\int_K w_n u = \int_K u^2$ .

Remark 3.2 (i) Theorem 5.4 remains valid for reflexive Banach space and continuity replaced by weaker condition, namely, weak lower semi-continuity. For proof, see Ekeland and Temam.

(ii) The set  $S$  of all solutions of (P) is closed and convex.

Verification Let  $u_1, u_2$  be two solutions of (P); that is,  $u_1, u_2 \in S$ .  $u_1 + (1-\lambda)u_2 \in K$ ;  $\lambda \in (0, 1)$  as  $K$  is convex. Since  $J$  is convex

$$J(u_1 + (1-\lambda)u_2) \leq \lambda J(u_1) + (1-\lambda)J(u_2)$$

Let  $\lambda = \inf_{v \in K} J(v) = J(u_1)$ , and  $\lambda = \inf_{v \in K} J(v) = J(u_2)$  then

$$J(u_1 + (1-\lambda)u_2) = \lambda J(u_1) + (1-\lambda)J(u_2)$$

that is,  $J(u_1 + (1-\lambda)u_2) = J(u_1)$  implying  $u_1 + (1-\lambda)u_2 \in S$ . Therefore,  $S$  is convex.

Let  $u_n$  be a sequence in  $S$  such that  $u_n \rightarrow u$ . For proving closedness, we need to show that  $u \in S$ . Since  $J$  is continuous

$$J(u) = \liminf_n J(u_n)$$

This gives

$$J(u) = J(u_1)$$

(iii) The solution of Theorem 5.4 is unique if  $J$  is strictly convex.

Verification Let  $u_1, u_2 \in S$  and  $u_1 \neq u_2$ . Then  $\frac{u_1 + u_2}{2} \in S$  as  $S$  is convex. Therefore,  $J(\frac{u_1 + u_2}{2}) = J(u_1) = J(u_2)$ . Since  $J$  is strictly convex

$$J(\frac{u_1 + u_2}{2}) < \frac{1}{2} J(u_1) + \frac{1}{2} J(u_2) = \frac{1}{2} J(u_1) + \frac{1}{2} J(u_1) = J(u_1)$$

This is a contradiction. Hence,  $u_1 = u_2$  is false and  $u_1 = u_2$ .

Quadratic and Convex Programming:

For  $K = \{v \in X; \sum_{i=1}^m c_i(v) \leq 0; \sum_{i=1}^m c_i(v) = 0; m+1 \leq i \leq m\}$ ; (P) is called a nonlinear programming problem. If  $c_i$  and  $J$  are convex functionals, then (P) is called a convex programming problem.

For  $X = \mathbb{R}^n$ ;  $K = \{v \in \mathbb{R}^n; \sum_{j=1}^m a_{ij} v_j \leq b_i; v_j \geq 0; i=1, \dots, m\}$ ; (P) is called a quadratic programming problem. If  $J(v) = \sum_{i=1}^n c_i v_i^2$ ;  $X = \mathbb{R}^n$ ;  $P = \{v \in \mathbb{R}^n; \sum_{j=1}^n a_{ij} v_j \leq b_i; v_j \geq 0; i=1, \dots, m\}$ ;  $A = (a_{ij})$  is a  $m \times n$  positive definite matrix, then  $P$  is called a linear programming problem.

### Calculus of Variations and Euler-Lagrange Equation :

The classical calculus of variation is a special case of (P) where we look for the extremum of functionals of the type

$$J(v) = \int_a^b F(x; u; u') dx \quad (i)$$

u is a twice continuously differentiable function on [a; b], F is continuous in x, u and u', and has continuous partial derivatives with respect to u and u'.

Theorem 4.1 A necessary condition for the functional J(u) to have an extremum at u is that u must satisfy the Euler-Lagrange equation

$$\frac{\partial F}{\partial u} - \frac{d}{dx} \left( \frac{\partial F}{\partial u'} \right) = 0 \tag{ii}$$

in [a; b] with boundary conditions u(a) and u(b) = .

Proof Let u(a) = u(b) = 0, then

$$J(u + v) - J(u) = \int_a^b [F(x; u + v; u') - F(x; u; u')] dx \tag{iii}$$

Using the Taylor series expansion

$$F(x; u + v; u') = F(x; u; u') + \left( \frac{\partial F}{\partial u} + v \frac{\partial^2 F}{\partial u^2} + \frac{\partial F}{\partial u'} + v' \frac{\partial^2 F}{\partial u' \partial u'} \right) v + \frac{1}{2!} \left( v \frac{\partial^3 F}{\partial u^3} + 2 v' \frac{\partial^3 F}{\partial u^2 \partial u'} + v'' \frac{\partial^3 F}{\partial u' \partial u'^2} \right) v^2 + \dots$$

it follows from (iii) that

$$J(u + v) - J(u) = \int_a^b \left[ \left( \frac{\partial F}{\partial u} + v \frac{\partial^2 F}{\partial u^2} + \frac{\partial F}{\partial u'} + v' \frac{\partial^2 F}{\partial u' \partial u'} \right) v + \frac{1}{2!} \left( v \frac{\partial^3 F}{\partial u^3} + 2 v' \frac{\partial^3 F}{\partial u^2 \partial u'} + v'' \frac{\partial^3 F}{\partial u' \partial u'^2} \right) v^2 + \dots \right] dx \tag{iv}$$

where the first and the second Frchet differentials are given by

$$dJ(u)(v) = \int_a^b \left( \frac{\partial F}{\partial u} + v \frac{\partial^2 F}{\partial u^2} + \frac{\partial F}{\partial u'} + v' \frac{\partial^2 F}{\partial u' \partial u'} \right) v dx \tag{v}$$

$$d^2J(u)(v) = \int_a^b \left( v \frac{\partial^3 F}{\partial u^3} + 2 v' \frac{\partial^3 F}{\partial u^2 \partial u'} + v'' \frac{\partial^3 F}{\partial u' \partial u'^2} \right) v dx \tag{vi}$$

The necessary condition for the functional J to have an extremum at u is that dJ(u)v = 0 for all v ∈ C<sup>2</sup>[a; b] such that v(a) = v(b) = 0; that is

$$0 = dJ(u)v = \int_a^b \left( \frac{\partial F}{\partial u} + v \frac{\partial^2 F}{\partial u^2} + \frac{\partial F}{\partial u'} + v' \frac{\partial^2 F}{\partial u' \partial u'} \right) v dx \tag{vii}$$

Integrating the second term in the integrand in (vii) by parts, we get

$$\int_a^b \left[ \frac{\partial F}{\partial u} + \frac{d}{dx} \left( \frac{\partial F}{\partial u'} \right) v \right] dx + \left[ v \frac{\partial F}{\partial u'} \right]_a^b = 0 \tag{viii}$$

Since v(a) = v(b) = 0, the boundary terms vanish and the necessary condition becomes

$$\int_a^b \left[ \frac{\partial F}{\partial u} + \frac{d}{dx} \left( \frac{\partial F}{\partial u'} \right) \right] v dx = 0 \text{ for all } v \in C^2[a; b] \tag{ix}$$

for all function v ∈ C<sup>2</sup>[a; b] vanishing at a and b. This is possible only if

$$\frac{d}{dx} \left( \frac{d}{dx} \right) = 0$$

$$\frac{d}{dx} \left( \frac{d}{dx} \right) = 0$$

### III. CONCLUSION

In this paper report, we have seen definitions of: optimization and related terms, general cases of optimization, some theorems, remarks and their proof was discussed. Optimization plays an important role not only in Mathematics. However in this research work, optimization gives easy way of modelling and solving real live problem thematically. Moreover, chapter one deals with general introduction of optimization, definition of optimization and related terms related term.

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