$E$-invexity and generalized $E$-invexity in $E$-differentiable multiobjective programming

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Abstract.

In this paper, a new concept of generalized convexity is introduced for not necessarily differentiable vector optimization problems. For an $E$-differentiable function, the concept of $E$-invexity is introduced as a generalization of the $E$-differentiable $E$-convexity notion. In addition, some properties of $E$-differentiable $E$-invex functions are investigated. Furthermore, the so-called $E$-Karush-Kuhn-Tucker necessary optimality conditions are established for the considered $E$-differentiable vector optimization problems with both inequality and equality constraints. Also, the sufficiency of the $E$-Karush-Kuhn-Tucker necessary optimality conditions are proved for such $E$-differentiable vector optimization problems in which the involved functions are $E$-invex and/or generalized $E$-invex.

Key Words: $E$-invex set; $E$-invex function; $E$-differentiable function; $E$-Karush-Kuhn-Tucker necessary optimality conditions.

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1 Introduction

Multiobjective programming, has grown remarkably in studying the development of optimality conditions. This is a consequence of the fact that many real world problems can be modeled as optimization problems with several objectives conflicting with one another, that is, by vector optimization problems. Although the concept of convexity plays a vital real in proving the fundamental results in optimization theory, however, not all real life problems can be analyzed as convex multiprojective programming problems. Therefore, various classes of nonconvex vector optimization problems have been defined in optimization literature. One of such important generalizations of the convexity notion is the concept of invexity introduced by Hanson [12]. In the case of differentiable scalar optimization problems. Namely, Hanson showed that, instead of the usual convexity assumption, if all functions are assumed to be invex (with respect to the same function $\eta$), then the sufficient optimality conditions and weak duality can be proved. Over the years, many generalizations of this concept have been introduced in the literature (see, for example, [2], [3], [4], [5], [6], [7], [8], [10], [11], [14], [15], [16], [20], [21], [22], [23], and others).

Craven and Glover [9] characterized the cone-invexity property, for differentiable functions, in terms of Lagrange multipliers. They also established Kuhn-Tucker type optimality conditions and duality theorems for cone invex programs. Jeyakumar and Mond [13] generalized Hanson’s definition to the vectorial case. They defined $V$-invexity of differentiable vector-valued functions which preserve the sufficient optimality conditions and duality results as in the scalar case and avoid the major difficulty of verifying that the inequality holds for the same function $\eta$ for invex functions in multiobjective programming problems.

Another generalization of convexity was derived by Youness [24]. Namely, he introduced the definition of an $E$-convex set and the definition of an $E$-convex function and analyzed some properties of these nonconvex sets and functions. Moreover, the results established by Youness [24] were improved by Yang [25]. Further, Megahed et al. [19] presented the concept of an $E$-differentiable convex function which transforms a (not necessarily) differentiable convex function to a differentiable function based on the effect of an operator $E : R^n \rightarrow R^m$.

In this paper, a new class of nonconvex $E$-differentiable vector optimization problems with both inequality and equality constraints is considered in which the involved functions are $E$-invex. Therefore, the concept of a so-called $E$-differentiable $E$-invex function for $E$-differentiable vector optimization problems is introduced. Further, under the introduced $E$-Guignard constraint qualification, the so-called $E$-Karush-Kuhn-Tucker necessary optimality conditions are established for the considered $E$-differentiable vector optimization problems with both inequality and equality constraints. It is also given an example of such a vector optimization problems with $E$-differentiable $E$-invex functions for which the $E$-Guignard constraint qualification is satisfied but the $E$-Abadie constraint qualification is not satisfied. It turns out that the $E$-Karush-Kuhn-Tucker necessary optimality conditions es-

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established for such a nonsmooth vector optimization problem are not satisfied in such a case. Moreover, the sufficient optimality conditions are derived for the considered E-differentiable vector optimization problem under E-invexity and/or generalized E-invexity. This result is illustrated by the example of nonconvex E-differentiable vector optimization problem in which the involved functions are E-invex (with respect to the same function \( \eta \)). Thus, in the present paper, tools of differentiable optimization problems are used in proving optimality conditions for (weakly) efficiency of nonsmooth multiobjective programming problems.

2 Preliminaries

Let \( \mathbb{R}^n \) be the \( n \)-dimensional Euclidean space and \( \mathbb{R}^n_+ \) be its nonnegative orthant. The following convention for equalities and inequalities will be used in the paper.

For any vectors \( x = (x_1, x_2, \ldots, x_n)^T \) and \( y = (y_1, y_2, \ldots, y_n)^T \) in \( \mathbb{R}^n \), we define:

(i) \( x \leq y \) if and only if \( x_i \leq y_i \) for all \( i = 1, 2, \ldots, n \);

(ii) \( x > y \) if and only if \( x_i > y_i \) for all \( i = 1, 2, \ldots, n \);

(iii) \( x \geq y \) if and only if \( x_i \geq y_i \) for all \( i = 1, 2, \ldots, n \);

(iv) \( x \geq y \) if and only if \( x \geq y \) and \( x \neq y \).

Now, we introduce the definition of an E-invex set as a generalization of an E-convex set given by Youness [24] and the definition of an invex set (with respect to \( \eta \)) given by Mohan and Neogy [21].

**Definition 1** Let \( E : \mathbb{R}^n \to \mathbb{R}^n \). A set \( M \subseteq \mathbb{R}^n \) is said to be an E-invex set (with respect to \( \eta : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n \)) if and only if there exists a vector-valued function \( \eta : M \times \mathbb{R}^n \to \mathbb{R}^n \) such that the relation

\[
E(u) + \lambda \eta(E(x), E(u)) \in M
\]

holds for all \( x, u \in M \) and any \( \lambda \in [0, 1] \).

**Remark 2** If \( \eta \) is a vector-valued function defined by \( \eta(z, y) = z - y \), then the definition of an E-invex set reduces to the definition of an E-convex set (see Youness [24]).

**Remark 3** If \( E(u) = u \), then the definition of an E-invex set with respect to the function \( \eta \) reduces to the definition of an invex set with respect to \( \eta \) (see Mohan and Neogy [21]).

Now, we present an example of such an E-invex set which is not E-convex.

**Example 4** Let \( M = [1, 9] \cup [-9, -1] \) and \( E : R \to R \) be an operator defined by

\[
E(x) = \begin{cases} 
  x^2 & \text{if } 0 \leq x \leq 3, \\
-3 & \text{if } -3 \leq x \leq 0, \\
-1 & \text{if } x < -3 \text{ or } x > 3.
\end{cases}
\]

and \( \eta : M \times \mathbb{R} \to \mathbb{R} \) be defined by

\[
\eta(E(x), E(u)) = \begin{cases} 
  x - u & \text{if } x \geq 0, u \geq 0, \\
-9 & \text{if } x > 0, u \leq 0, \\
1 & \text{if } x < 0, u \geq 0.
\end{cases}
\]

Then, by Definition 1, \( M \) is an E-invex set with respect to the function \( \eta \) given above. However, it is not E-convex as can be seen by taking \( x = 1, u = 4, \lambda = \frac{1}{2} \), we have

\[
\lambda E(x) + (1 - \lambda) E(u) = 0 \notin M.
\]

Hence, by the definition of an E-convex set (see Remark 2), it follows that \( M \) is not E-convex.

Now, we present an example of such an E-invex set with respect to \( \eta \) which is not invex with respect to \( \eta \).

**Example 5** Let \( M = [1, 4] \cup [-4, -1] \) and \( E : R \to R \) be an operator defined by

\[
E(x) = \begin{cases} 
  x^2 & \text{if } -2 \leq x \leq 2, \\
-1 & \text{if } x < -2 \text{ or } x > 2.
\end{cases}
\]

and \( \eta : M \times \mathbb{R} \to \mathbb{R} \) be defined by

\[
\eta(x, u) = \begin{cases} 
  x - u & \text{if } x \leq u, \\
-4 & \text{if } x > u.
\end{cases}
\]

Then, by Definition 1, \( M \) is an E-invex set with respect to the function \( \eta \) given above. However, it is not invex with respect to \( \eta \) as can be seen by taking \( x = -1, u = 1, \lambda = \frac{1}{2} \), we have

\[
u + \lambda \eta(x, u) = 0 \notin M.
\]

Hence, by the definition of an invex set (see Remark 3), it follows that \( M \) is not an invex set with respect to \( \eta \).

**Definition 6** [19] Let \( E : \mathbb{R}^n \to \mathbb{R}^n \) and \( f : M \to \mathbb{R} \) be a (not necessarily) differentiable function at a given point \( u \in M \). It is said that \( f \) is an E-differentiable function at \( u \) if and only if \( f \circ E \) is a differentiable function at \( u \) (in the usual sense) and, moreover,

\[
(f \circ E)(x) = (f \circ E)(u) + \nabla (f \circ E)(u)(x - u) + \theta(u, x - u) \|x - u\|,
\]

where \( \theta(u, x - u) \to 0 \) as \( x \to u \).

Now, we introduce a new concept of generalized convexity for E-differentiable vector-valued functions.

**Definition 7** Let \( E : \mathbb{R}^n \to \mathbb{R}^n \) and \( f : M \to \mathbb{R} \) be an E-differentiable function on a nonempty open set \( M \subseteq \mathbb{R}^n \). It is said that \( f \) is E-invex with respect to \( \eta \) at \( u \in M \) on \( M \) if, there exists \( \eta : M \times \mathbb{R} \to \mathbb{R} \) such that, for all \( x \in M \),

\[
f_i(E(x)) - f_i(E(u)) \geq \nabla f_i(E(u)) \eta_i(E(x), E(u)), \quad i = 1, \ldots, k.
\]

(2)

If inequalities (2) hold for any \( u \in M \), then \( f \) is E-invex with respect to \( \eta \) on \( M \).

**Remark 8** From Definition 7, there are special cases:

a) If \( f \) is a differentiable function and \( E(x) \equiv x \) (\( E \) is an identity map), then the definition of an E-invex function reduces to the definition of an invex function introduced by Hanson [12] in the scalar case.
b) If \( M \times M \to R^n \) is defined by \( \eta(x, u) = x - u \), then we obtain the definition of an E-differentiable E-convex vector-valued function introduced by Megahed et al. [19].

c) If \( f \) is differentiable, \( E(x) = x \) and \( \eta(x, u) = x - u \), then the definition of an E-invex function reduces to the definition of a differentiable convex vector-valued function.

d) If \( f \) is differentiable and \( \eta(x, u) = x - u \), then we obtain the definition of a differentiable E-convex function introduced by Youness [24].

**Definition 9** Let \( E : R^n \to R^n \) and \( f : M \to R^n \) be an E-differentiable function on a nonempty open set \( M \subset R^n \). It is said that \( f \) is strictly E-invex with respect to \( \eta \) at \( u \in M \) on \( M \) if, there exists \( \eta : M \times M \to R^n \) such that, for all \( x \in M \) with \( E(x) \neq E(u) \), the inequalities

\[
f_i(E(x)) - f_i(E(u)) > \nabla f_i(E(u)) \eta(E(x), E(u)), \quad i = 1, ..., k,
\]

hold. If inequalities (3) are fulfilled for any \( u \in M \) \( E(x) \neq E(u) \), then \( f \) is strictly E-invex with respect to \( \eta \) on \( M \).

Now, we present an example of such an E-invex function which is not E-convex.

**Example 10** Let \( f : [0, \frac{\pi}{2}] \to R \) be defined by \( f(x) = \cos x \) and \( E : [0, \frac{\pi}{2}] \to [0, \frac{\pi}{2}] \) be an operator defined by \( E(x) = \frac{\pi}{2} - x \) and \( \eta \) be defined by

\[
\eta(E(x), E(u)) = \begin{cases} 
\sin u - \sin x & \text{if } x > u, \\
0 & \text{if } x = u, \\
2 \sin x - 2 \sin u & \text{if } x < u.
\end{cases}
\]

Then \( f \) is E-invex on \([0, \frac{\pi}{2}]\), but it is not E-convex as can be seen by taking \( x = 0, u = \frac{\pi}{4} \), and \( \lambda = \frac{1}{2} \), since the inequality

\[
f(\lambda E(x) + (1 - \lambda) E(u)) \geq \lambda f(E(x)) + (1 - \lambda) f(E(u))
\]

holds. Hence, by the definition of an E-invex function [24], it follows that \( f \) is not E-convex on \([0, \frac{\pi}{2}]\).

Now, we give the necessary condition for E-differentiable E-invexity.

**Proposition 11** Let \( E : R^n \to R^n \) and \( f : M \to R^n \) be an E-invex (strictly E-invex) function with respect to \( \eta \) on \( M \) and \( u \in M \). Further, assume that \( f \) is E-differentiable at \( u \). Then, the following inequality

\[
\nabla f(E(x)) - \nabla f(E(u)) \eta(E(x), E(u)) \geq 0,
\]

holds for all \( x, u \in M \) \( E(x) \neq E(u) \).

Now, we prove a sufficient condition for an E-differentiable E-invex function with respect to \( \eta \).

**Theorem 12** Let \( E : R^n \to R^n \) and \( f : M \to R \) be an E-differentiable function at \( u \in M \) on \( M \). Further, assume that there exists \( \eta : M \times M \to R^n \), such that

\[
f(E(u) + \lambda \eta(E(x), E(u))) \leq f(E(x)) + (1 - \lambda) f(E(u)),
\]

holds for any \( \lambda \in [0, 1] \). Then, \( f \) is an E-invex function with respect to \( \eta \).

**Proof.** By (5), we have that the inequality

\[
f(E(u) + \lambda \eta(E(x), E(u))) - f(E(u)) \leq \\
\lambda[f(E(x)) - f(E(u))]
\]

holds for any \( \lambda \in [0, 1] \). Thus, the above inequality yields for any \( \lambda \in [0, 1],
\]

\[
f(E(u) + \lambda \eta(E(x), E(u))) - f(E(u)) \leq \\
\lambda[f(E(x)) - f(E(u))].
\]

By assumption, \( f \) is E-differentiable at \( u \). Hence, by Definition 6, it follows that \( f \circ E \) is differentiable at \( u \). Therefore, letting \( \lambda \to 0 \), we obtain the inequality (2).

Now, we introduce various classes of generalized E-differentiable E-invex functions as a generalization of appropriate generalized E-convex functions and, thus, pseudo-convex and quasi-convex functions.

**Definition 13** Let \( E : R^n \to R^n \) and \( f : M \to R^n \) be an E-differentiable function on a nonempty open set \( M \subset R^n \). It is said that \( f \) is pseudo E-invex with respect to \( \eta \) at \( u \in M \) on \( M \) if, there exists \( \eta : M \times M \to R^n \) such that, for all \( x \in M \) and \( i = 1, ..., k, \)

\[
f_i(E(x)) < f_i(E(u)) \implies \nabla f_i(E(u)) \eta(E(x), E(u)) < 0.
\]

If (8) holds for any \( u \in M \), then \( f \) is pseudo E-invex with respect to \( \eta \) on \( M \).

**Definition 14** Let \( E : R^n \to R^n \) and \( f : M \to R^n \) be an E-differentiable function on a nonempty open set \( M \subset R^n \). It is said that \( f \) is strictly pseudo E-invex with respect to \( \eta \) at \( u \in M \) on \( M \) if, there exists \( \eta : M \times M \to R^n \) such that, for all \( x \in M \) and \( i = 1, ..., k, \)

\[
f_i(E(x)) \leq f_i(E(u)) \implies \nabla f_i(E(u)) \eta(E(x), E(u)) < 0.
\]

Note that every strictly pseudo E-invex function is pseudo E-invex and every E-differentiable pseudo E-invex function is pseudo E-invex. Also, every pseudo E-invex function is E-invex and every E-invex function is pseudo E-invex function for the same function \( \eta \), but the converse is not true.

Now, we present an example of such an E-differentiable pseudo E-invex function which is not E-invex.

**Example 15** Let \( f : (0, \infty) \to R \) be defined by \( f(x) = \log x \), \( \eta : (0, \infty) \times (0, \infty) \to R \) be defined by \( \eta(x, u) = \sqrt{x} - \sqrt{u} \) and \( E : (0, \infty) \to (0, \infty) \) be an operator defined by \( E(x) = x^3 \). Further, assume that \( (f \circ E)(x) < (f \circ E)(u) \). Thus, we have \( f(E(x)) = \log x < \log u = f(E(u)) \).

This implies that \( x < u \) for all \( x, u \in (0, \infty) \). Moreover, we have \( \nabla (f \circ E)(u) \eta(E(x), E(u)) < 0 \). Therefore, by Definition 13, \( f \) is an E-differentiable pseudo E-invex function. Indeed, if we set \( x = 10, u = 1 \), then we have

\[
f(E(x)) - f(E(u)) = 1 < \nabla f(E(u)) \eta(E(x), E(u)) = 9.
\]

Hence, by Definition 2, it follows that \( f \) is not E-invex.
Let $E : \mathbb{R}^n \to \mathbb{R}^n$ and $f : M \to \mathbb{R}^n$ be an E-differentiable function on a nonempty open set $M \subset \mathbb{R}^n$. It is said that $f$ is quasi-E-invex with respect to $\eta$ at $u \in M$ on $M$ if, there exists $\eta : M \times M \to \mathbb{R}^n$ such that, for all $x \in M$ and $i = 1, \ldots, k$,

\[
\frac{f_i(E(x)) - f_i(E(u))}{\|E(x) - E(u)\|} \leq 0 \Rightarrow \nabla f_i(E(u))\eta(E(x), E(u)) \leq 0.
\] (10)

If (10) holds for any $u \in M$, then $f$ is quasi-E-invex with respect to $\eta$ on $M$.

Note that E-differentiable quasi-E-convex is trivially quasi E-convex and every pseudo E-invex function is quasi E-invex.

Now, we present an example of such a quasi E-invex function but not a quasi E-convex function.

Example 17 Let $f : [0, \frac{\pi}{2}] \to \mathbb{R}$ be defined by $f(x) = \cos x$, $E : [0, \frac{\pi}{2}] \to [0, \frac{\pi}{2}]$ be an operator defined by $E(x) = \frac{\pi}{2} - x$ and $\eta$ defined by $\eta(E(x), E(u)) = x - u$. It can be shown that $f$ is quasi E-invex on $[0, \frac{\pi}{2}]$. Assume that $(f \circ E)(x) \leq (f \circ E)(u)$. We have $(f \circ E)(x) = \sin x \leq \sin u = (f \circ E)(u)$. This inequality implies that $x \leq u$. Hence, we have $\nabla (f \circ E)(u)\eta(E(x), E(u)) = \cos(u - x) \geq 0$. Therefore, by the definition of quasi E-convexity, $f$ is not quasi E-convex on $[0, \frac{\pi}{2}]$.

3 E-optimality conditions for E-differentiable multiobjective programming

In some cases, the multiobjective programming problem can be represented as the following unconstrained vector optimization problem:

\[
\min f(x) = (f_1(x), \ldots, f_p(x)) \quad \text{subject to} \quad x \in M,
\]

where $M$ is a nonempty set of $\mathbb{R}^n$, and $f$ denotes a vector-valued E-differentiable function on $M$.

Now, we give the definitions of a weak Pareto solution and a Pareto solution of the considered vector optimization problem (VP).

Definition 18 A feasible point $\bar{x}$ is said to be a weak Pareto (weakly efficient) solution of (VP) if and only if there exists no feasible point $x$ such that $f(x) < f(\bar{x})$.

Definition 19 A feasible point $\bar{x}$ is said to be a Pareto (efficient) solution of (VP) if and only if there exists no feasible point $x$ such that $f(x) \leq f(\bar{x})$.

Let $E : \mathbb{R}^n \to \mathbb{R}^n$ be an one-to-one and onto operator. For the considered multiobjective programming problem (VP), we define the vector optimization problem (VP$_E$) as follows

\[
\min f(E(x)) = (f_1(E(x)), \ldots, f_p(E(x))) \quad \text{subject to} \quad x \in E(M),
\]

where $E(M)$ is a nonempty set of $\mathbb{R}^n$, and $f \circ E$ denotes a vector-valued differentiable function on $E(M)$.

Now, we give the definitions of a weak Pareto (weakly efficient) solution and a Pareto (efficient) solution of the vector optimization problem (VP$_E$), which are at the same time a weak E-Pareto solution (weakly E-efficient solution) and an E-Pareto solution (E-efficient solution) of the considered multiobjective programming problem (VP).

Definition 20 A feasible point $E(\bar{x})$ is said to be a weak E-Pareto solution (weakly E-efficient solution) of (VP) if and only if there exists no feasible point $E(x)$ such that $f(E(x)) < f(E(\bar{x}))$.

Definition 21 A feasible point $E(\bar{x})$ is said to be an E-Pareto solution (E-efficient solution) of (VP) if and only if there exists no feasible point $E(x)$ such that $f(E(x)) \leq f(E(\bar{x}))$.

As it is known [6], a characteristic property of a scalar invex function with respect to $\eta$ is the fact that each its stationary point is also its global minimum. It turns out that this property can be generalized to the class of vector E-invex functions with respect to $\eta$. For this purpose, we have to define adequately an E-critical point concept for vector-valued functions.

Definition 22 Let $E : \mathbb{R}^n \to \mathbb{R}^n$. A point $u \in M$ is said to be a vector E-critical point of an E-differentiable vector-valued function $f : M \to \mathbb{R}^p$, (or, in other words, for the problem (VP)) if there exists a vector $\lambda \in \mathbb{R}^p$ with $\lambda \geq 0$ such that $\lambda^T \nabla (f \circ E)(u) = 0$.

Now, we prove that every weakly efficient point is also an E-vector critical point.

Theorem 23 Let $E : \mathbb{R}^n \to \mathbb{R}^n$ and $f : M \to \mathbb{R}^p$ be an E-differentiable vector-valued function, $E(\bar{x})$ is a weakly E-efficient solution of (VP). Then, there exists a vector $\bar{\lambda} \in \mathbb{R}^p$ with $\bar{\lambda} \geq 0$ such that $\bar{\lambda}^T \nabla (f \circ E)(\bar{x}) = 0$.

Proof. Suppose that $\bar{\lambda}^T \nabla (f \circ E)(\bar{x}) \neq 0$. Then, let $d = -\nabla (f \circ E)(\bar{x})$. Hence, we obtain

\[
\nabla (f \circ E)(\bar{x})d = -\|\nabla (f \circ E)(\bar{x})\|^2 < 0. \tag{11}
\]

By assumption, the objective function $f$, is E-differentiable at $\bar{x}$. Thus, by Definition 6, we get

\[
(f \circ E)(x) = (f \circ E)(\bar{x}) + \nabla (f \circ E)(\bar{x})^T (x - \bar{x}) + \theta(\bar{x}, x - \bar{x})\|x - \bar{x}\|. \tag{12}
\]
Using \( \theta(x, x - \bar{x}) \to 0 \) and \( \frac{x - \bar{x}}{\|x - \bar{x}\|} \to d \) as \( x \to \bar{x} \) together with (11), we get that the following inequality

\[
(f \circ E)(x) < (f \circ E)(\bar{x}).
\]

holds, which is a contradiction to the assumption that \( E(\bar{x}) \) is a weakly \( E \)-efficient solution of the vector optimization problem (VP). Hence, there exists a vector \( \lambda \in \mathbb{R}^n \) with \( \lambda \geq 0 \) such that \( \lambda^T \nabla (f \circ E)(\bar{x}) = 0 \). The proof of this theorem is completed. \( \blacksquare \)

Now, we prove the converse of the above theorem using the concept of vectorial \( E \)-invexity introduced in the paper.

**Theorem 24** Let \( E : \mathbb{R}^n \to \mathbb{R}^m, \bar{x} \) be a vector \( E \)-critical point of (VP), and let \( f \circ E \) be a vector \( E \)-invex function at \( \bar{x} \) with respect to \( \eta \). Then \( \bar{x} \) is a weak \( E \)-Pareto solution of (VP).

**Proof.** Let \( \bar{x} \) be a vector \( E \)-critical point. Then, there exists a vector \( \lambda \in \mathbb{R}^n \) with \( \lambda \geq 0 \) such that \( \lambda^T \nabla f(\bar{x}) = 0. \) We proceed by contradiction. Suppose that \( \bar{x} \) is not a weak \( E \)-Pareto solution of (VP). Then, there exists another point \( \bar{\bar{x}} \in \mathbb{R}^n \) such that

\[
(f \circ E)(\bar{x}) < (f \circ E)(\bar{\bar{x}}).
\]

Thus, by \( E \)-invexity of \( f \), we get that

\[
f(\bar{x}) - f(\bar{\bar{x}}) \geq \nabla f(\bar{x}) \eta(\bar{x}, \bar{\bar{x}}).
\]

Combining (13) and (14), we get that the inequality

\[
\lambda^T \nabla (f \circ E)(\bar{x}) < 0,
\]

holds, which is a contradiction to the assumption that \( \bar{x} \) is a weak Pareto solution for (VP). The proof of this theorem is completed. \( \blacksquare \)

In general, a vector optimization problem is considered with the set of inequality and equality constraints as follows

\[
\begin{align*}
\text{minimize} & \quad f(x) = (f_1(x), \ldots, f_p(x)) \\
\text{subject to} & \quad g_i(x) \leq 0, \quad i \in I = \{1, \ldots, m\}, \\
& \quad h_j(x) = 0, \quad j \in T = \{1, \ldots, s\}, \\
& \quad x \in X,
\end{align*}
\]

where \( X \) is a nonempty convex open subset of \( \mathbb{R}^n \), \( f_i : X \to \mathbb{R}, i \in I = \{1, \ldots, p\}, g_j : X \to \mathbb{R}, j \in J, h_j : X \to \mathbb{R}, j \in T \), are real-valued \( E \)-differentiable functions defined on \( X \). For the purpose of simplifying our presentation, we will next introduce some notations which will be used frequently throughout this paper. We will write \( g := (g_1, \ldots, g_m) : X \to \mathbb{R}^m \) and \( h := (h_1, \ldots, h_s) : X \to \mathbb{R}^s \) for convenience. Let

\[
\Omega := \{ x \in \mathbb{R}^n : g_j(x) \leq 0, \quad j \in J, h_j(x) = 0, \quad t \in T \}
\]

be the set of all feasible solutions of (CVP). Further, let us denote by \( J(x) \), the set of inequality constraint indices that are active at a feasible solution \( x \), that is, \( J(x) := \{ j \in J : g_j(x) = 0 \} \). Let \( E : \mathbb{R}^n \to \mathbb{R}^s \) be an one-to-one and onto operator. For the considered constrained multiobjective program-

\[ (\text{CVP})_E \]

ming problem (CVP), we define its associated constrained vector optimization problem (CVP\(_E\)) with both inequality and equality constraints as follows

\[
\begin{align*}
\text{minimize} & \quad f(E(x)) = (f_1(E(x)), \ldots, f_p(E(x))) \\
\text{subject to} & \quad g_j(E(x)) \leq 0, \quad j = 1, \ldots, m, \\
& \quad h_t(E(x)) = 0, \quad t = 1, \ldots, s, \\
& \quad x \in X,
\end{align*}
\]

where the set \( X \) and the functions \( f_i, i \in I, g_j, j \in J, h_t, t \in T \), are defined in the similar way as for (CVP). We call (CVP\(_E\)) the \( E \)-vector optimization problem (associated to the multiobjective programming problem (CVP)). Let

\[
\Omega_E := \{ x \in \mathbb{R}^n : g_j(E(x)) \leq 0, \quad j \in J, \\
& \quad h_t(E(x)) = 0, \quad t \in T \}
\]

be the set of all feasible solutions of (CVP\(_E\)).

In this section, we derive both necessary and sufficient optimality conditions for a new class of nonconvex multicriteria optimization problems. Namely, we consider a class of \( E \)-differentiable multiobjective programming problems. Throughout this section, \( E : \mathbb{R}^n \to \mathbb{R}^s \) is assumed to be an one-to-one and onto operator. By Definition 6, the functions constituting the \( E \)-vector optimization problem (CVP\(_E\)) are differentiable at any of its feasible solution (in the usual sense). Further, we denote by \( J_E(x) \), the set of inequality constraint indices that are active at a feasible solution \( E(x) \), that is, \( J_E(x) := \{ j \in J : g_j(E(x)) = 0 \} \). Moreover, it can be proved [1] (see Lemma 25 below) that if \( \bar{x} \) is a (weak) Pareto solution of the \( E \)-vector optimization problem (CVP\(_E\)), then \( \bar{x} \) is a (weak) Pareto solution of the original multiobjective programming problem (CVP). We call \( \bar{x} \) a (weak) \( E \)-Pareto solution of the problem (CVP).

**Lemma 25** [1] Let \( E : \mathbb{R}^n \to \mathbb{R}^s \) be a one-to-one and onto and \( \bar{x} \in \Omega_E \) be a weak Pareto (Pareto) solution of the constrained \( E \)-vector optimization problem (CVP\(_E\)). Then \( \bar{x} \) is a weak \( E \)-Pareto solution of the constrained multiobjective programming problem (CVP).

Before we establish the Karush-Kuhn-Tucker necessary optimality conditions for problem (CVP), we re-call the Motzkin’s theorem of the alternative.

**Theorem 26** [18] (Motzkin’s theorem of the alternative). Let \( A, C, D \) be given matrices, with \( A \) being nonvacuous. Then either the system of inequalities

\[
Ax < 0, \quad Cx \not\leq 0, \quad Dx = 0
\]

has a solution \( x \), or the system

\[
A^T y_1 + C^T y_2 + D^T y_3 = 0, \quad y_1 \geq 0, y_2 \geq 0
\]

has solution \( y_1, y_2 \) and \( y_3 \), but neither both.
Now, we give the definition of the minimal element of a given set (with respect to an order relation).

**Definition 27** [17] Let \( Y \) be a given set in \( \mathbb{R}^n \) ordered by \( \preceq \) or by \( \prec \). Specifically, we call the minimal element of \( Y \) defined by \( \prec \) a minimal vector, and that defined by \( \preceq \) a weak minimal vector. Formally speaking, a vector \( \overline{y} \in Y \) is called a minimal vector in \( Y \) if there exists no vector \( y \in Y \) such that \( y \preceq \overline{y} \); it is called a weak minimal vector if there exists no vector \( y \in Y \) in such that \( y \prec \overline{y} \).

**Definition 28** Let \( Y \subseteq \mathbb{R}^n \). The Bouligand contingent cone of \( Y \) at \( \overline{y} \in Y \) is the set \( T_Y(\overline{y}) \) of all vectors \( q \in \mathbb{R}^n \) such that there exist a sequence \( \{y_n\} \subset Y \) and a sequence \( \{\beta_n\} \) of strictly positive real numbers such that

\[
\lim_{n \to \infty} y_n = \overline{y}, \quad \lim_{n \to \infty} \beta_n = 0, \quad \lim_{n \to \infty} \frac{y_n - \overline{y}}{\beta_n} = q.
\]

In other words, the Bouligand contingent cone of \( Y \) at \( \overline{y} \) is defined by

\[
T_Y(\overline{y}) = \{d \in \mathbb{R}^n : \exists \beta_n > 0, \exists y_n \in Y \to \overline{y} s.t. \beta_n(y_n - \overline{y}) \to d\}.
\]

A vector \( d \in \mathbb{R}^n \) belonging to \( T_Y(\overline{y}) \) is called a tangent direction to \( Y \) from \( \overline{y} \in \mathbb{R}^n \).

**Remark 29** Note that Lin [17] named any Bouligand contingent vector, that is, any vector \( q \in T_Y(\overline{y}) \), a convergence vector for the set \( Y \) at \( \overline{y} \).

Now, we extend the result established by Lin [17] for the E-vector optimization problem (CVP).

**Theorem 30** If \( \overline{x} \in \Omega_E \) is locally (weak) minimal for \( f \circ E \) on \( \Omega_E \), then no Bouligand contingent vector for \( f(E(\Omega_E)) \) at \( \overline{y} = f(E(\overline{x})) \) is strictly negative.

**Definition 31** The tangent cone (also called contingent cone or Bouligand cone) of \( \Omega_E \) at \( \overline{x} \in \partial \Omega_E \) is defined by

\[
T_{\Omega_E}(\overline{x}) = \{d \in \mathbb{R}^n : \exists \beta_n > 0, d_n \to d, \exists \beta_n > 0, d_n \in \partial \Omega_E\}.
\]

Before we prove the Karush-Kuhn-Tucker necessary optimality conditions for the differentiable constrained E-vector optimization problem with inequality and equality constraint (CVP), we introduce the so-called E-Guignard constraint qualification. In order to do this, for the constrained E-vector optimization problem (CVP), we introduce the E-linearized cone \( L_E(\overline{x}) \).

**Definition 32** For the constrained E-vector optimization problem (CVP), the E-linearized cone at \( \overline{x} \in \Omega_E \), denoted by \( L_E(\overline{x}) \), is defined by

\[
L_E(\overline{x}) = \{d \in \mathbb{R}^n : \nabla g_j(E(\overline{x}))d \leq 0, j \in J_E(\overline{x}), \nabla h_i(E(\overline{x}))d = 0, t \in T\}.
\]

It is easy to see that \( L_E(\overline{x}) \) is a nonempty closed convex cone.

The following lemma shows the relationship between the Bouligand contingent cone \( T_{\Omega_E}(\overline{x}) \) and the E-linearizing \( L_E(\overline{x}) \) cone.

**Lemma 33** If \( \overline{\gamma} \in \Omega_E \) is a Pareto solution of the constrained E-vector optimization problem (CVP), then

\[
\text{cl cone } T_{\Omega_E}(\overline{\gamma}) \subseteq L_E(\overline{\gamma}).
\]

**Proof.** Let \( \overline{\gamma} \in \Omega_E \) be given and \( d \in T_{\Omega_E}(\overline{\gamma}) \). Then, by Definition 31, there exists a sequence \( \{x_n\} \subset \Omega_E \) such that \( \lim_{n \to \infty} x_n = \overline{\gamma}, \lim_{n \to \infty} \beta_n = 0, \lim_{n \to \infty} \frac{x_n - \overline{\gamma}}{\beta_n} = d \). By assumption, all constraint functions \( g_j, j \in J_E(\overline{x}), t \in T \), are E-differentiable at \( \overline{\gamma} \). Hence, by Definition 6, it follows that

\[
g_j(E(x_n)) = g_j(E(\overline{\gamma})) + \nabla g_j(E(\overline{\gamma}))^T(x_n - \overline{\gamma}) + \theta g_j(\overline{\gamma}, x_n - \overline{\gamma})\|x_n - \overline{\gamma}\|, j \in J_E(\overline{\gamma}),
\]

\[
h_i(E(x_n)) = h_i(E(\overline{\gamma})) + \nabla h_i(E(\overline{\gamma}))^T(x_n - \overline{\gamma}) + \theta_h_i(\overline{\gamma}, x_n - \overline{\gamma})\|x_n - \overline{\gamma}\|, t \in T,
\]

where \( \theta g_j(\overline{\gamma}, x_n - \overline{\gamma}) \to 0, j \in J_E(\overline{\gamma}), \theta_h_i(\overline{\gamma}, x_n - \overline{\gamma}) \to 0, t \in T \), as \( x_n \to \overline{\gamma} \). Assume that \( d_n := \frac{x_n - \overline{\gamma}}{\beta_n} \). Then \( x_n = \overline{\gamma} + \beta_n d_n \) and we obtain that

\[
g_j(E(x_n)) = g_j(E(\overline{\gamma} + \beta_n d_n)) \leq 0 = g_j(E(\overline{\gamma})), j \in J_E(\overline{\gamma}),
\]

\[
h_i(E(x_n)) = h_i(E(\overline{\gamma} + \beta_n d_n)) = 0 = h_i(E(\overline{\gamma})), t \in T.
\]

From (18), (19), and Definition 31, it follows that

\[
\nabla g_j(E(\overline{\gamma}))d \leq 0, j \in J_E(\overline{\gamma}),
\]

\[
\nabla h_i(E(\overline{\gamma}))d = 0, t \in T.
\]

By (20), (21) and Definition 32, we have \( T_{\Omega_E}(\overline{\gamma}) \subseteq L_E(\overline{\gamma}) \).

Since \( L_E(\overline{\gamma}) \) is closed and convex, we get

\[
\text{cl cone } T_{\Omega_E}(\overline{\gamma}) \subseteq L_E(\overline{\gamma}).
\]

Now, we give the so-called E-Abadie constraint qualification for the E-differentiable vector optimization problem (CVP) with both inequality and equality constraints which was introduced in [1].

**Definition 34** It is said that the so-called E-Abadie constraint qualification (\( ACQ_E \)) holds at \( \overline{x} \in \Omega_E \) for the differentiable E-vector optimization problem (CVP) with both inequality and equality constraints if

\[
T_{\Omega_E}(\overline{x}) = L_E(\overline{x}).
\]

Now, we introduce the so-called E-Guignard constraint qualification for the E-differentiable constrained vector optimization problem (CVP) with both inequality and equality constraints.
Definition 35 It is said that the so-called \(E\)-Guignard constraint qualification (\(GQC_E\)) holds at \( \bar{x} \in \Omega_E \) for the differentiable constrained \(E\)-vector optimization problem (\(CVP_E\)) with both inequality and equality constraints if
\[
cl \, \mathop{conv} \, T_{\Omega_E}(\bar{x}) = L_{E}(\bar{x}).\tag{23}
\]

Now, we present an example of such a nondifferentiable vector optimization problem for which the \(E\)-Guignard constraint qualification is satisfied but \(E\)-Abadie constraint qualification introduced in [1] does not hold.

Example 36 Consider the following nonconvex nondifferentiable vector optimization problem

\[
\begin{align*}
\text{minimize} & \quad f(x) = (2x_2 - 2\sqrt{x_1}, -\sqrt{x_1}x_2) \\
\text{s.t.} & \quad g(x) = x_2 - \sqrt{x_1}x_2 \leq 0.
\end{align*}
\]

(CVP(1))

Note that \( \Omega = \{ (x_1, x_2) \in \mathbb{R}^2 : x_2 - \sqrt{x_1}x_2 \leq 0 \} \). Let \( E : \mathbb{R}^2 \to \mathbb{R}^2 \) be an one-to-one and onto mapping defined as follows \( E(x_1, x_2) = (x_1^2, x_2) \). For the considered vector optimization problem (\(CVP(1)\)), we define its associated \(E\)-vector optimization problem (\(CVP(E)\)) as follows

\[
\begin{align*}
\text{minimize} & \quad f(E(x)) = (2x_2 - 2x_1, -x_1x_2) \\
\text{subject to} & \quad g(E(x)) = x_2 - x_1 \leq 0.
\end{align*}
\]

Note that \( \Omega_E = \{ (x_1, x_2) \in \mathbb{R}^2 : x_2 - x_1 \leq 0 \} \) and \( \bar{x} = (0, 0) \) is a feasible solution. Then, by the definition of the \(E\)-linearized cone, we have that \( L_E(\bar{x}) = \{ d_1, d_2 \in \mathbb{R}^2 : d_2 \leq d_1 \} \). Further, by the definition of the Bouligand contingent cone, we have that \( T_{\Omega_E}(\bar{x}) = \{ (d_1, d_2) \in \mathbb{R}^2 : -d_2 \leq 0 \land d_1 \leq d_2 \} \). Therefore, \( L_E(\bar{x}) = cl \, \mathop{conv} \, T_{\Omega_E}(\bar{x}) \) but \( L_E(\bar{x}) \not\subseteq T_{\Omega_E}(\bar{x}) \). Hence, the \(E\)-Guignard constraint qualification is satisfied at \( \bar{x} \) but \( E\)-Abadie constraint qualification is not satisfied.

Now, we prove the Karush-Kuhn-Tucker necessary optimality conditions for the differentiable constrained \(E\)-vector optimization problem (\(CVP_E\)) and, thus, the so-called \(E\)-Karush-Kuhn-Tucker necessary optimality conditions for not necessarily differentiable constrained multiobjective programming problem (\(CVP\)) in which the involved functions are \(E\)-differentiable and for which the \(E\)-Guignard constraint qualification holds.

Theorem 37 (\(E\)-Karush-Kuhn-Tucker necessary optimality conditions). Let \( \bar{x} \in \Omega_E \) be a weak Pareto solution of the constrained \(E\)-vector optimization problem (\(CVP_E\)) (and, thus, \( E(\bar{x}) \) be a weak \(E\)-Pareto solution of the considered multiobjective programming problem (\(CVP\))). Further, let \( f, g, h \) be \(E\)-differentiable at \( \bar{x} \) and the \(E\)-Guignard constraint qualification be satisfied at \( \bar{x} \). Then there exist Lagrange multipliers \( \lambda \in \mathbb{R}^n, \mu \in \mathbb{R}^m, \xi \in \mathbb{R}^s \) such that

\[
\begin{align*}
\sum_{i=1}^{p} \lambda_i \nabla (f_i \circ E)(\bar{x}) + \sum_{j=1}^{m} \mu_j \nabla (g_j \circ E)(\bar{x}) + \\
\sum_{i=1}^{s} \xi_i \nabla (h_i \circ E)(\bar{x}) = 0,
\end{align*}
\]

\( p, m \), \( s \) such that

\[
\begin{align*}
\sum_{i=1}^{p} \lambda_i \nabla (f_i \circ E)(\bar{x}) + \sum_{j=1}^{m} \mu_j \nabla (g_j \circ E)(\bar{x}) + \\
\sum_{i=1}^{s} \xi_i \nabla (h_i \circ E)(\bar{x}) = 0,
\end{align*}
\]

\( \gamma_j(\bar{x}) = 0, \ j \in J(\bar{x}) \),

\( \bar{T} \geq 0, \bar{\mu} \geq 0 \).

Proof. By assumption, \( \bar{x} \in \Omega_E \) is a weak Pareto solution in the \(E\)-vector optimization problem (\(VP_E\)) (and, thus, \( E(\bar{x}) \) is a weak \(E\)-Pareto solution of the considered multiobjective programming problem (\(VP\))). Let \( d \in T_{\Omega_E}(\bar{x}) \) and \( x_n \) be the corresponding sequence of feasible solutions in \(E\)-vector optimization problem (\(VP_E\)) converging to \( \bar{x} \) and \( \beta_n \) be the corresponding sequence of scalars such that \( \beta_n > 0 \) for each integer \( n \) converging to \(0\) (see Definition 31). We denote by \( f(E(\bar{x})) \subseteq \mathbb{R}^k \) and \( \bar{g} = f(E(\bar{x})) \). Since \( \bar{x} \in \Omega_E \) is a weak Pareto point in the \(E\)-vector optimization problems (\(VP_E\)), \( \bar{g} = f(E(\bar{x})) \) is a weak minimal vector in \( f(E(\Omega_E)) \) (see Theorem 30). Further, we consider the sequence of vectors \( (y_n) \in f(E(\Omega_E)) \), where \( y_n = f(E(x_n)) \). By assumption, the objective functions \( f_i, i \in I \), are \(E\)-differentiable at \( \bar{x} \). Thus, by Definition 6, we have

\[
\begin{align*}
(f_i(\bar{x}) - f_i(x_n)) + \theta_i(\bar{x}, x_n - \bar{x}) \frac{\|x_n - \bar{x}\|}{\beta_n},
\end{align*}
\]

\( \theta_i(\bar{x}, x_n - \bar{x}) \to 0, i \in I, \) as \( x_n \to \bar{x} \). By the above equality, we obtain, for any \( i \in I \),

\[
\begin{align*}
\frac{y_n - \bar{g}}{\beta_n} &= \frac{1}{\beta_n}((f_i(\bar{x}) - f_i(x_n)) - (f_i(\bar{x}) - \bar{g})) \\
&= \nabla (f_i(\bar{x}) - \bar{g})(\bar{x}) \frac{\|x_n - \bar{x}\|}{\beta_n} + \theta_i(\bar{x}, x_n - \bar{x}) \frac{\|x_n - \bar{x}\|}{\beta_n}.
\end{align*}
\]

(28)

By assumption, \( \{x_n\} \) is a sequence of feasible solutions in the constrained \(E\)-vector optimization problems (\(CVP_E\)) converging to \( \bar{x} \). In view of \(E\)-differentiability of the functions \( f_i, i \in I \), at \( \bar{x} \), it follows that \( (f \circ E) \) is differentiable at \( \bar{x} \) and, hence, it is also a continuous function at \( \bar{x} \). Therefore, the sequence \( (y_n) \) converges to \( \bar{g} = f(E(\bar{x})) \). Hence, by (28), follows that

\[
\begin{align*}
q = \lim_{n \to \infty} \frac{y_n - \bar{g}}{\beta_n} = \nabla (f_i \circ E)(\bar{x}) \frac{d}{d}.
\end{align*}
\]

Then, by Definition 31, \( q \) is a Bouligand contingent vector for \( f(E(\Omega_E)) \) at \( \bar{g} \). From the \(E\)-Guignard constraint qualification, it follows that \( d \) is a Bouligand contingent vector (convergence vector) for \( \Omega_E \) at \( \bar{x} \) if and only if \( d \) is a solution to the system

\[
\begin{align*}
\nabla (f_j(\bar{x}) \circ E)(\bar{x}) \frac{d}{d} \leq 0, & \ j \in J, \\
\nabla (h_i(\bar{x}) \circ E)(\bar{x}) \frac{d}{d} \leq 0, & \ i \in I.
\end{align*}
\]

(30)

Since \( \bar{g} \) is a weak Pareto of \( f(E(\Omega_E)) \), there is no Bouligand contingent (convergence vector) for \( f(E(\Omega_E)) \) at \( \bar{g} \) strictly negative (see Theorem 30). Therefore, the system

\[
\begin{align*}
\nabla (f_j(\bar{x}) \circ E)(\bar{x}) \frac{d}{d} < 0, & \ i \in I, \\
\nabla (g_j(\bar{x}) \circ E)(\bar{x}) \frac{d}{d} \leq 0, & \ j \in J, \\
\nabla (h_i(\bar{x}) \circ E)(\bar{x}) \frac{d}{d} = 0, & \ i \in T.
\end{align*}
\]

(32)

(33)

(34)
is inconsistent. From Motzkin’s theorem of the alternative (see Theorem 26), it follows that the system

\[
\sum_{i=1}^{p} \bar{T}_i \nabla (f_i \circ E)(\bar{\tau}) + \sum_{j \in \mathcal{R}(\bar{\tau})} \bar{\mu}_j \nabla (g_j \circ E)(\bar{\tau}) + \sum_{i=1}^{p} \bar{\xi}_i \nabla (h_i \circ E)(\bar{\tau}) = 0,
\]

\[
\bar{\tau} \in \mathbb{R}^p, \quad \bar{\tau} \geq 0, \quad \bar{\mu} \in \mathbb{R}^{\mathcal{R}(\bar{\tau})}, \quad \bar{\xi} \in \mathbb{R}^p
\]

is consistent. Let \((\bar{\tau}, \bar{\mu}, \bar{\xi})\) be a solution to the above system. Then, we define \(\bar{\zeta} \in \mathbb{R}_+\) as follows

\[
\bar{\zeta}_j = \bar{\mu}_j, \quad j \in J(E(\bar{\tau})),
\]

\[
\bar{\zeta}_j = 0, \quad j \notin J(E(\bar{\tau})).
\]

Thus, we conclude that \((\bar{\tau}, \bar{\mu}, \bar{\xi})\) satisfies the E-Karush-Kuhn-Tucker necessary optimality conditions (24)-(26). Hence, the proof of this theorem is completed. \(\square\)

In order to show that the E-Karush-Kuhn-Tucker necessary optimality conditions cannot be fulfilled without the E-Guignard constraint qualification, we present the example of such an E-differentiable vector optimization problem.

**Example 38** Consider the following nondifferentiable vector optimization problem

\[
f(x) = (f_1(x), f_2(x)) = (\sin \sqrt{x_1}, \cos x_2 + \sqrt{x_1^2}) \to \text{V-min}
\]

\[
g(x) = \sin \sqrt{x_1} - \cos x_2 \leq 0,
\]

\[
h(x) = \sqrt{T}(\bar{\xi} - x_2) = 0.
\]

Note that the set of all feasible solutions of the considered constrained vector optimization problem (CVP2) is \(\Omega = \{(x_1, x_2) \in \mathbb{R}^2 : \sin \sqrt{x_1} - \cos x_2 \leq 0, \sqrt{T}(\bar{\xi} - x_2) = 0\}\). Further, note that the functions constituting problem (CVP2) are nondifferentiable at \((0, 0)\). It can be shown by Definition 19 that the feasible solution \(\bar{T} = (0, 0)\) is an E-Pareto solution of the considered nondifferentiable constrained multijob programming problem (CVP2).

Let \(E : \mathbb{R}^2 \to \mathbb{R}^2\) be defined as follows: \(E(x_1, x_2) = (x_1^2, x_2 - x_1^2)\). For the considered constrained vector optimization problem (CVP2), we define its associated constrained E-vector optimization problem (CVP2E) as follows

\[
f(E(x)) = (f_1(E(x)), f_2(E(x))) = (\sin x_1, \sin x_2 + x_1^2) \to \text{V-min}
\]

\[
g(E(x)) = \sin x_1 - \sin x_2 \leq 0, \quad (CVP2E)
\]

\[
h(E(x)) = x_1 x_2 = 0.
\]

Note that the set of all feasible solutions of the constructed constrained E-vector optimization problem (CVP2E) is \(\Omega_E = \{(x_1, x_2) \in \mathbb{R}^2 : \sin x_1 - \sin x_2 \leq 0 \land x_1 x_2 = 0\}\) and \(\eta(E(x), E(u)) = (2 \sin x_1, 2 \sin x_2)\). Then, by the definition of the E-linearized cone, we have that \(L_E(\bar{T}) = \{(d_1, d_2) \in \mathbb{R}^2 : d_2 \geq d_1\}\). Further, by the definition of the Bouligand contingent cone, we have that \(T_{\Delta_E}(\bar{T}) = \{(d_1, d_2) \in \mathbb{R}^2 : d_2 \geq 0 \land d_1 \leq 0 \land d_2 = 0\}\). Therefore, \(L_E(\bar{T}) \neq cl \text{cont} T_{\Delta_E}(\bar{T})\). Hence, the E-Guignard constraint qualification is not satisfied at \(\bar{T}\). Now, we show that E-Karush-Kuhn-Tucker necessary optimality conditions are not satisfied at \(\bar{T}\). Indeed, we have \(\nabla (f_i \circ E)(\bar{T}) = [0, 1]^T\), \(\nabla (f_2 \circ E)(\bar{T}) = [0, 1]^T\), \(\nabla (g \circ E)(\bar{T}) = [1, -1]^T\), \(\nabla (h \circ E)(\bar{T}) = [0, 0]^T\). However, note that the E-Karush-Kuhn-Tucker necessary optimality conditions are not satisfied at \(\bar{T} = (0, 0)\). Namely, by (24), it follows that \(\bar{\lambda}_1 + \bar{\lambda}_2 = 0\), are fulfilled only in the case when \(\bar{\lambda}_1 = 0\) and \(\bar{\lambda}_2 = 0\), what is impossible.

**Definition 39** \((E(\bar{T}), \bar{\tau}, \bar{\mu}, \bar{\xi}) \in \Omega \times \mathbb{R}^p \times \mathbb{R}^m \times \mathbb{R}^q\) is said to be an E-Karush-Kuhn-Tucker point for the considered constrained vector optimization problem (CVP) if the E-Karush-Kuhn-Tucker necessary optimality conditions (24)-(26) are satisfied at \(E(\bar{T})\) with Lagrange multipliers \(\bar{\lambda}, \bar{\mu}, \bar{\xi}\).

**Definition 40** \((\bar{T}, \bar{\tau}, \bar{\mu}, \bar{\xi}) \in \Omega_E \times \mathbb{R}^p \times \mathbb{R}^m \times \mathbb{R}^q\) is said to be a Karush-Kuhn-Tucker point for the considered constrained E-vector optimization problem (CVP) if the Karush-Kuhn-Tucker necessary optimality conditions (24)-(26) are satisfied at \(\bar{T}\) with Lagrange multipliers \(\bar{\lambda}, \bar{\mu}, \bar{\xi}\).

Now, we prove the sufficiency of the E-Karush-Kuhn-Tucker necessary optimality conditions for constrained vector optimization problem (CVP) under E-invexity hypotheses.

**Theorem 41** Let \((\bar{T}, \bar{\tau}, \bar{\mu}, \bar{\xi}) \in \Omega \times \mathbb{R}^p \times \mathbb{R}^m \times \mathbb{R}^q\) be a Karush-Kuhn-Tucker point of the constrained E-vector optimization problem (CVP). Let \(T_E^+(E(\bar{T})) = \{t \in T : \bar{\xi}^T t > 0\}\) and \(T_E^-(E(\bar{T})) = \{t \in T : \bar{\xi}^T t < 0\}\). Furthermore, assume the following hypotheses are fulfilled:

- **a)** each objective function \(f\) is an E-invex with respect to \(\eta\) at \(\bar{T}\) on \(\Omega_E\);
- **b)** each inequality constraint \(g_j\), \(j \in J(E(\bar{T}))\), is an E-invex function with respect to \(\eta\) at \(\bar{T}\) on \(\Omega_E\);
- **c)** each equality constraint \(h_t\), \(t \in T^+(E(\bar{T}))\), is an E-invex function with respect to \(\eta\) at \(\bar{T}\) on \(\Omega_E\);
- **d)** each function \(-h_t\), \(t \in T^-(E(\bar{T}))\), is an E-invex function with respect to \(\eta\) at \(\bar{T}\) on \(\Omega_E\).

Then \(\bar{T}\) is a weak Pareto solution of the problem (CVP) and, thus, \(E(\bar{T})\) is a weak E-Pareto solution of the problem (CVP).

**Proof.** By assumption, \((\bar{T}, \bar{\tau}, \bar{\mu}, \bar{\xi}) \in \Omega_E \times \mathbb{R}^p \times \mathbb{R}^m \times \mathbb{R}^q\) is a Karush-Kuhn-Tucker point of the constrained E-vector optimization problem (CVP). Then, by Definition 40, the Karush-Kuhn-Tucker necessary optimality conditions (24)-(26) are satisfied at \(\bar{T}\) with Lagrange multipliers \(\bar{\lambda}, \bar{\mu}, \bar{\xi}\). We proceed by contradiction. Suppose, contrary to the result, that \(\bar{T}\) is not a weak Pareto
solution of the problem (CVP). Hence, by Definition 18, there exists another \( \tilde{x} \in \Omega_E \) such that

\[
f_i(E(\tilde{x})) < f_i(E(x)).
\] (35)

Using hypotheses a)-d), by Definition 7 and Theorem 12, the following inequalities

\[
f_i(E(\tilde{x})) - f_i(E(x)) \geq \nabla f_i(E(x)) \eta(E(\tilde{x}), E(x)), \quad i \in I,
\] (36)

\[
g_j(E(\tilde{x})) - g_j(E(x)) \geq \nabla g_j(E(x)) \eta(E(\tilde{x}), E(x)), \quad j \in J(E(x)),
\] (37)

\[
h_j(E(\tilde{x})) - h_j(E(x)) \geq \nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)), \quad j \in J(E(x)),
\] (38)

\[
-\nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)), \quad j \in J(E(x)),
\] (39)

hold, respectively. Combining (35)-(36) and then multiplying the resulting inequalities by the corresponding Lagrange multipliers and adding both their sides, we get

\[
\sum_{i=1}^{m} \lambda_i \nabla (f_i \circ E)(x) \eta(E(\tilde{x}), E(x)) < 0.
\] (40)

Multiplying inequalities (37)-(39) by the corresponding Lagrange multipliers, respectively, we obtain

\[
\mu_i g_i(E(\tilde{x})) - \mu_i g_i(E(x)) \geq 0,
\] (41)

\[
\xi_j h_j(E(\tilde{x})) - \xi_j h_j(E(x)) \geq 0,
\] (42)

\[
\xi_j \nabla h_j(E(\tilde{x})) \eta(E(\tilde{x}), E(x)), \quad \xi_j \nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)),
\] (43)

Using the E-Karush-Kuhn-Tucker necessary optimality condition (25) together with \( \tilde{x} \in \Omega_E \) and \( x \in \Omega_E \), we get, respectively,

\[
\mu_i \nabla g_i(E(x)) \eta(E(\tilde{x}), E(x)) \leq 0, \quad j \in J(E(x)),
\] (44)

\[
\xi_j \nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)) \leq 0, \quad j \in J(E(x)),
\] (45)

\[
\xi_j \nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)) \leq 0, \quad j \in J(E(x)).
\] (46)

Adding both sides of the above inequalities, by (40), we obtain that the following inequality

\[
\sum_{i=1}^{m} \lambda_i \nabla (f_i \circ E)(x) + \sum_{j=1}^{m} \mu_i \nabla g_j(E(x))
\]

\[
+ \xi_j \nabla h_j(E(x)) \eta(E(\tilde{x}), E(x)) < 0
\]

holds, which is a contradiction to the the E-Karush-Kuhn-Tucker necessary optimality condition (24). By assumption, \( E : R^n \to R^n \) is an one-to-one and onto operator. Since \( \tilde{x} \) is a weak Pareto solution of the problem (CVP), by Lemma 25, \( E(\tilde{x}) \) is a weak E-Pareto solution of the problem (CVP). Thus, the proof of this theorem is completed. \( \Box \)

\textbf{Remark 42} As it follows from the proof of Theorem 41, the sufficient conditions are also satisfied if all or some of the functions \( g_j, j \in J(E(x)), h_i, t \in T^+(E(x)), h_i, t \in T^-(E(x)) \) are E-differentiable quasi E-invex function at \( \tilde{x} \) on \( \Omega \) with respect to \( \eta \).

\textbf{Theorem 43} Let \( (\tilde{x}, \lambda, \mu, \tilde{\xi}) \in \Omega_E \times R^n \times R^m \times R^d \) be a Karush-Kuhn-Tucker point of the constrained E-vector optimization problem (CVP). Furthermore, assume that the following hypotheses are fulfilled:

a) each objective function \( f \) is strictly E-invex with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

b) each inequality constraint \( g_j, j \in J(E(x)) \), is an E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

c) each equality constraint \( h_i, t \in T^+(E(x)) \), is an E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

d) each function \( -h_i, t \in T^-(E(x)) \), is an E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

Then \( \tilde{x} \) is a Pareto solution of the problem (CVP) and, thus, \( E(\tilde{x}) \) is an E-Pareto solution of the problem (CVP).

Now, under the concepts of generalized E-invexity, we prove the sufficient optimality conditions for a feasible solution to be a weak E-Pareto solution of problem (CVP).

\textbf{Theorem 44} Let \( (\tilde{x}, \lambda, \mu, \tilde{\xi}) \in \Omega_E \times R^n \times R^m \times R^d \) be a Karush-Kuhn-Tucker point of the constrained E-vector optimization problem (CVP). Furthermore, assume that the following hypotheses are fulfilled:

a) each objective function \( f \) is a pseudo E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

b) each inequality constraint \( g_j, j \in J(E(x)) \), is a quasi E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

c) each equality constraint \( h_i, t \in T^+(E(x)) \), is a quasi E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

d) each function \( -h_i, t \in T^-(E(x)) \), is an quasi E-invex function with respect to \( \eta \) at \( \tilde{x} \) on \( \Omega_E \).

Then \( \tilde{x} \) is a weak Pareto solution of the problem (CVP) and, thus, \( E(\tilde{x}) \) is a weak E-Pareto solution of the problem (CVP).

\textbf{Proof} By assumption, \( (\tilde{x}, \lambda, \mu, \tilde{\xi}) \in \Omega_E \times R^n \times R^m \times R^d \) is a Karush-Kuhn-Tucker point in the considered constrained E-vector optimization problem (CVP). Then, by Definition 40, the Karush-Kuhn-Tucker necessary optimality conditions (24)-(26) are satisfied at \( \tilde{x} \) with Lagrange multipliers \( \lambda \in R^p, \mu \in R^m \) and \( \tilde{\xi} \in R^d \). We proceed by contradiction. Suppose, contrary to the result, that \( \tilde{x} \) is not a weak Pareto solution in problem (CVP). Hence, by Definition 19, there exists another \( \tilde{x} \in \Omega_E \) such that

\[
f_i(E(\tilde{x})) \leq f_i(E(x)), \quad i \in I.
\] (47)
By hypothesis (a), the objective function \( f \) is \( E \)-differentiable pseudo \( E \)-invex at \( \bar{x} \) on \( \Omega_{E} \). Then, (47) gives
\[
\nabla (f_i \circ E) (\bar{x}) \eta (E(\bar{x}), E(\bar{x})) < 0, \quad i \in I,
\]
(48)

By the E-Karush-Kuhn-Tucker necessary optimality condition (26), inequality (48) yields
\[
\left[ \sum_{i=1}^{p} \lambda_i \nabla (f_i \circ E) (\bar{x}) \right] \eta (E(\bar{x}), E(\bar{x})) < 0.
\]
(49)

Since \( E(\bar{x}) \in \Omega \), \( E(\bar{x}) \in \Omega \), therefore, the E-Karush-Kuhn-Tucker necessary optimality conditions (25) and (26) imply
\[
g_j(E(\bar{x})) - g_j(E(\bar{x})) \leq 0, \quad j \in J(E(\bar{x})).
\]
From the assumption, each \( g_j \), \( j \in J \), is an \( E \)-differentiable quasi \( E \)-invex function at \( \bar{x} \) on \( \Omega_{E} \). Then, by Definition 16, we get
\[
\nabla g_j(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0, \quad j \in J(E(\bar{x})).
\]
(50)

Thus, by the E-Karush-Kuhn-Tucker necessary optimality condition (26), and by Definition 16, (50) gives
\[
\sum_{j \in J(E(\bar{x}))} \mu_j \nabla g_j(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0.
\]
Hence, taking into account \( \mu_j = 0 \), \( j \notin J(E(\bar{x})) \), we have
\[
\sum_{j \in J(E(\bar{x}))} \mu_j \nabla g_j(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0.
\]
(51)

From \( \bar{x} \in \Omega \), \( \bar{x} \in \Omega \), \( \bar{x} \in E(\bar{x}) \) and \( \bar{x} = E(\bar{x}) \), we get
\[
h_t(E(\bar{x})) - h_t(E(\bar{x})) = 0, \quad t \in T^+(E(\bar{x})),
\]
\[
-h_t(E(\bar{x})) - (-h_t(E(\bar{x}))) = 0, \quad t \in T^-(E(\bar{x})).
\]
(52)

Since each equality constraint \( h_t \), \( t \in T^+(E(\bar{x})) \), and each function \( -h_t \), \( t \in T^-(E(\bar{x})) \), is an \( E \)-differentiable quasi \( E \)-invex function at \( \bar{x} \) on \( \Omega_{E} \), then by Definition 16, (52) and (53) give, respectively,
\[
\nabla h_t(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0, \quad t \in T^+(E(\bar{x})),
\]
(54)
\[
-\nabla h_t(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0, \quad t \in T^-(E(\bar{x})).
\]
(55)

Thus, (54) and (55) yield
\[
\left[ \sum_{t \in T^+(E(\bar{x}))} \bar{\xi}_t \nabla h_t(E(\bar{x})) \right] \eta (E(\bar{x}), E(\bar{x})) \leq 0,
\]
\[
+ \sum_{t \in T^-(E(\bar{x}))} \bar{\xi}_t \nabla h_t(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0.
\]
Hence, taking into account \( \bar{\xi}_t = 0 \), \( t \notin T^+(E(\bar{x})) \cup T^-(E(\bar{x})) \), we have
\[
\sum_{t \in T} \bar{\xi}_t \nabla h_t(E(\bar{x})) \eta (E(\bar{x}), E(\bar{x})) \leq 0.
\]
(56)

Combining (49), (51) and (56), we get that the following inequality
\[
\left[ \sum_{i=1}^{p} \lambda_i \nabla (f_i \circ E)(\bar{x}) + \sum_{j \in J(E(\bar{x}))} \mu_j \nabla g_j(E(\bar{x})) \right] \eta (E(\bar{x}), E(\bar{x})) \leq 0.
\]
which is a contradiction to the E-Karush-Kuhn-Tucker necessary optimality condition (24). The result that \( E(\bar{x}) \) is a weak \( E \)-Pareto solution follows directly from Lemma 25. Thus, the proof of this theorem is completed.

In order to illustrate the sufficient optimality conditions established in the paper, we now present an example of an \( E \)-differentiable vector optimization problem in which the involved functions are (generalized) \( E \)-invex.

**Example 45** Consider the following nondifferentiable vector optimization problem
\[
f(x) = (f_1(x), f_2(x)) = (\sqrt{x_1} - \cos x_2 + 4, \sqrt{x_1} - \cos x_2 + 2) \rightarrow V \min
\]
\[
g_1(x) = \sin \sqrt{x_1} - 4 \cos x_2 + \frac{\pi}{2} \leq 0,
\]
\[
g_2(x) = 2 \sin \sqrt{x_1} + 7 \cos x_2 + \sqrt{x_1} - 6 \leq 0,
\]
\[
g_3(x) = 4 \sqrt{x_1} + 4(\frac{\pi}{2} - x_2)^2 - 9 \leq 0,
\]
\[
g_4(x) = 2 \sqrt{x_1} + 2(\frac{\pi}{2} - x_2) - 3 \leq 0,
\]
\[
g_5(x) = - \sin \sqrt{x_1} \leq 0,
\]
\[
g_6(x) = - \cos x_2 \leq 0.
\]

Note that the set of all feasible solutions of the considered vector optimization problem (VP3) is
\[
\Omega = \{(x_1, x_2) \in \mathbb{R}^2 : \sin \sqrt{x_1} - 4 \cos x_2 + \frac{24}{7} \leq 0,
\]
\[
2 \sin \sqrt{x_1} + 7 \cos x_2 + \sqrt{x_1} - 6 \leq 0, 4 \sqrt{x_1} + 4(\frac{\pi}{2} - x_2)^2 - 9 \leq 0,
\]
\[
2 \sqrt{x_1} + 2(\frac{\pi}{2} - x_2) - 3 \leq 0, \quad \sin \sqrt{x_1} \geq 0, \quad \cos x_2 \geq 0\}.
\]

Further, note that the functions constituting problem (VP3) are nondifferentiable at \( 0, \cos^{-1} \frac{\pi}{2} \). Let \( \eta(x, u) = \left( \frac{\sin (\sqrt{x_1} - \cos x_2)}{\sin \sqrt{x_1} - \cos x_2}, \frac{\sin \sqrt{x_1} - \cos x_2}{\sin \sqrt{x_1} - \cos x_2} \right), u \neq 0 \) and \( E : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \) be an one-to-one and onto mapping defined as follows \( E(x_1, x_2) = (\sqrt{x_1}, \frac{\pi}{2} - x_2) \). Now, for the considered \( E \)-invex nondifferentiable constrained multiobjective programming problem (CVP3), we define its associated constrained \( E \)-vector optimization problem (CVP_E3) as fol-
\[ f(E(x)) = (f_1(E(x)), f_2(E(x))) = (x_1 - \sin x_2 + 4, x_1 - \sin x_2 + 2) \rightarrow V-\min \]
\[ g_1(E(x)) = x_1 - 4 \sin x_2 + 2 \frac{\pi}{2} \leq 0, \]

\[ g_2(E(x)) = 2 \sin x_1 + 7 \sin x_2 + x_1 - 6 \leq 0, \]
\[ g_3(E(x)) = 4x_1^2 + 4x_2^2 - 9 \leq 0, \]
\[ g_4(E(x)) = 2x_1 + 2x_2 - 3 \leq 0, \]
\[ g_5(E(x)) = -\sin x_1 \leq 0, \]
\[ g_6(E(x)) = -\sin x_2 \leq 0. \]

Note that the set of all feasible solutions of the considered E-vector optimization problem (VP,E,3) is
\[ \Omega_E = \{(x_1, x_2) \in \mathbb{R}^2 : \sin x_1 - 4 \sin x_2 + \frac{24}{7} \leq 0, \]
\[ 2 \sin x_1 + 7 \sin x_2 + x_1 - 6 \leq 0, \quad 4x_1^2 + 4x_2^2 - 9 \leq 0, \]
\[ 2x_1 + 2x_2 - 3 \leq 0, \quad \sin x_1 \geq 0, \quad \sin x_2 \geq 0, \]

and \( \left(0, \sin^{-1} \frac{\pi}{2}\right) \) is a feasible solution of the problem (CVP,E,3). Further, note that all functions constituting the considered vector optimization problem (CVP,E,3) are E-differentiable E-inverse at \( (0, \sin^{-1} \frac{\pi}{2}) \). Then, it can also be shown that the E-Karush-Kuhn-Tucker necessary optimality conditions (24)-(26) are fulfilled at \( (0, \sin^{-1} \frac{\pi}{2}) \) with Lagrange multipliers \( \lambda_1 + \lambda_2 = 1, \lambda_2 = \frac{1}{7}, \) and \( \mu_5 = \frac{10}{7} \). Further, it can be proved that \( f, g_1, \) and \( g_2 \) are an E-inverse function at \( \nabla \) on \( \Omega_E \), the constraint function \( g_1, g_2 \) are quasi E-inverse at \( \nabla \) on \( \Omega_E \), the function \( g_3, g_4 \) are (strictly) pseudo E-invers at \( \nabla \) on \( \Omega_E \). Hence, \( \nabla = \left(0, \sin^{-1} \frac{\pi}{2}\right) \) is a Pareto solution of the E-vector optimization problem (CVP,E,3) and, thus, it is a E-Pareto solution of the considered multiobjective programming problem (CVP,E,3).

4 Concluding remarks
In this paper, a new class of nonconvex nondifferentiable vector optimization problems has been defined. Namely, an E-differentiable multiobjective programming problem with both inequality and equality constraint has been considered. Further, the so-called E-Karush-Kuhn-Tucker necessary optimality conditions with both inequality and equality constraints under the introduced E-Guisnard constraint qualification have been established for the considered E-differentiable vector optimization problem. Moreover, the sufficient optimality conditions have been derived for such nonconvex nonsmooth vector optimization problems under the introduced concepts of E-inverse and generalized E-inverse. In order to illustrate the optimality results established in the paper, the examples of E-differentiable multiobjective programming problems have been given.

However, some interesting topics for further research remain. It would be of interest to investigate whether it is possible to prove similar results for other classes of E-differentiable vector optimization problems. We shall investigate these questions in subsequent papers.

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