

A Non-Smooth Optimization Framework For Fault-Tolerant Control of Power Electronic Systems

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Abstract

Power electronic converters used for renewable energy integration are usually based on the algorithm that may fail to work in case of open-circuit or short-circuit faults of the semiconductor devices. The traditional approaches to control, such as linear quadratic control, and model predictive control, assume that dynamics are smooth. However, that cease to be valid in the presence of faults that lead to discontinuities in the topological sense. This article presents a unified approach to non-smooth optimization where the process of deciding the switching mode and analyzing the fault is viewed as a part of the variational problem. The dynamics of the switched system are described by using differential inclusions, while optimization is necessary to minimize tracking errors, power, and thermal stress by means of Clarke generalized gradient. The optimality conditions are derived by using parameters of finite dimensional variational problem using the approach based on Fritz-John condition, while a Lyapunov function is constructed to demonstrate the convergence of the state trajectory to the closed invariant set in the presence of faults. A proximal bundle algorithm that is designed specifically for the chosen inclusion is applied in this paper, while the convergence is guaranteed due to the property of semi-smoothness. The numerical experiments show performance of the algorithms in terms of the reduction of tracking error values and sliding mode accuracy in course of many iterations making evidence of high validity of the proposed approach for different cases of switches failures.

Keywords: Non-smooth optimization, Clarke subdifferential, variational inequality, fault-tolerant control, power electronic systems, switched dynamical systems, proximal bundle method.

1. Introduction

Power electronic converters are responsible for facilitating communication between renewable energy sources such as solar energy panels, wind turbines, energy storage systems, batteries, and the electric transmission system, while ensuring the correct functioning of this intermediary step, making it possible to ensure the effective integration of renewables into the grid structure (Kamil et al., 2024). With the increasing integration of distributed generation, the use of various types of multilevel and multi-phase converters is developing, with semiconductor switch malfunctioning constituting the major cause of failures influencing the service of such infrastructure as mobile cell networks operating with diesel and hybrid energy plants (Kamil et al., 2024). As a result, fault-tolerant

operation of the systems in question should be treated as a necessary requirement for the design of the power systems ensuring successful integration of renewable energy sources, thus stimulating considerable research efforts in the area of the so-called reconfiguration schemes of the power systems supporting big data transfer using the chimp optimization method as well as other similar bio-inspired ecosystems (Zhu et al., 2025). Recent advances in the field of condition monitoring that can be illustrated by deep learning and GIS techniques used in predictive maintenance for electromechanical systems show that there is a tendency to integrate fault anticipating design into the system control design rather than to consider fault detection and control as separate systems (Mishra et al., 2024).

The common smooth-control methodologies such as linear-quadratic regulators and model predictive control are crafted under the assumption of continuous differentiability of the system dynamics and cost functional. A practical example proving this limitation of the technique is represented by three-phase permanent-magnet synchronous machine drives production equipped with open-switch faults, which require the combination of modified control mechanism on top of the usual smooth controller to ensure effective control in the present conditions since the latter cannot deal with the abrupt change in the input matrix pair caused by breakdown (Chen et al., 2024). Similarly occurring problems of reconfiguration were experienced in the process of developing a robust controlled suspension, which was based on knowledge-data-fusion technologies, and sliding-mode control of photovoltaic maximum-power-point tracking systems since the systems under consideration needed the handling of the issue of non-linearities by means of switching-surface functions and not with the help of corresponding variational principles (Zhu et al., 2023; Kodirova et al., 2025). In addition, it has been presented that Lyapunov's adaptive sliding mode control of DC/DC converters under uncertainty conditions and robust sliding-mode control of single-polar inverters have taught that slides are capable of dealing with bounded uncertainty but the result was achieved without solving the problem by means of optimization principles (Gohar Ali et al., 2020; Sahraoui et al., 2025). Examples of non-singular fast sliding-mode technology for drives running on permanent-magnet synchronous motors and integer-order control for boost converters operating within systems based on the combination of supercapacitor-energy storing systems and conventional batteries made it possible to enhance the reliability of the technique while maintaining the significance of separation between fault-tolerant and normal control objectives (Awais et al., 2021; Yan & Hu, 2025). At the same time, terminal filtered integral sliding-mode backstepping control based on extended observer shows the efficiency of non-smooth control technology which has found its applications not only in the power-electronics field (Wang et al., 2018; Tran et al., 2020; Bhattacharya & Kapoor, 2024).

The gap identified in this body of work is that there is no universal non-smooth optimization framework that would allow for the representation of the switching mode of operation and fault occurrences as an inclusion in a single variational inequality problem, but rather as a conventional smooth controller with an additional fault detection and reconfiguration layer. In the subsequent sections, fault-tolerant control is introduced as a non-smooth optimization problem characterized by a penalty functional, the terms of which encapsulate the tracking error, energy use, and thermal constraints.

2. Mathematical preliminaries and system modeling

2.1. Switched system representation

Power converter dynamics under discrete operational modes are represented as a switched linear system in equation (1)

$$\dot{x}(t) = A\sigma x(t) + B\sigma u(t), \quad \sigma(t) \in \{1, 2, \dots, N\} \quad (1)$$

In this equation, $x(t)$ is the state vector, which consists of the voltages of capacitors and currents of inductors. The variable $u(t)$ is the control input and σ takes values in the set $\{1, \dots, N\}$ where the signal σ describes switching among the pairs of matrices $(A\sigma, B\sigma)$. Under normal circumstances, the variable σ is determined by a modulation strategy and under the fault conditions the number of matrix pairs decreases because switching devices that are unable to switch are excluded.

2.2. Fault representation as a set-valued modification

The occurrence of a switch fault can be modeled as not an exogenous disturbance but rather as a change in the set of inputs permissible in the system. Denoting by $U \subset \mathbb{R}^m$ the nominal control constraint set and by $F \subseteq \{1, \dots, N\}$ the index set of fault-affected modes, the fault-constrained admissible set is in equation (2)

$$UF(t) = \{u \in U : u \text{ is consistent with } (A\sigma, B\sigma), \sigma(t) \notin F\} \quad (2)$$

The nature of this fault allows it to be correctly incorporated in optimization problems as a restriction on the available control inputs rather than as an additional disturbance to the system dynamics. This formulation accounts for total converter leg failure (the case of open-circuit fault) and forced conduction (the case of short-circuit fault) σ values from $\{1, \dots, N\} \setminus F$.

2.3 Clarke Subdifferential and Non-smooth Structure

The performance purpose of the controller must penalize the tracking error, control effort and thermal stress, as the thermal constraint and switching cost make the resulting integrand non-differentiable during the periods of switching modes. For a locally Lipschitz function $\varphi : \mathbb{R}^k \rightarrow \mathbb{R}$, the Clarke generalized directional derivative at a point z in direction d is in equation (3)

$$\varphi^\circ(z; d) = \limsup_{y \rightarrow z, t \downarrow 0} \frac{[\varphi(y + td) - \varphi(y)]}{t} \quad (3)$$

and the Clarke subdifferential is the set in equation (4)

$$\partial\varphi(z) = \{ \xi \in \mathbb{R}^k : \langle \xi, d \rangle \leq \varphi^\circ(z; d) \text{ for all } d \in \mathbb{R}^k \} \quad (4)$$

In the case where φ is convex, the subdifferential $\partial\varphi(z)$ is the same as the classical subdifferential; for continuously differentiable functions $\varphi(z)$, $\partial\varphi(z)$ is reduced to the unique point $\{\nabla\varphi(z)\}$. The problem of non-smoothness introduced in the objective function due to the effect of switching is fully resolved through equations (3)-(4); thus, there is no need for smoothing techniques that will compromise the validity of optimality conditions that were derived in Section IV.

3. Variational Formulation of the Fault-Tolerant Control Problem

3.1. Objective functional

The fault-tolerant control synthesis problem is posed as minimization, over admissible control trajectories $u(\cdot) \in UF$, of the functional in equation (5)

$$f(u) = \int_0^T L(x(t), u(t), \sigma(t)) dt + \Phi(x(T)) \quad (5)$$

Here L represents a cost function that combines a quadratic tracking-error term, a penalty for the actuation effort of the l^1 -type that encourages sparse actuation reallocation across the non-injured legs, and the penalty for violating the thermal restriction modeled as an indicator function. Thus, the function $\Phi(x(T))$ imposes the penalty for the deviation from the desired end-point of the trajectory. The l^1 and indicator terms in L make the cost function L non-smooth with respect to u , thus necessitating its treatment using generalized differential calculus in Section 2.3 rather than classical gradient techniques.

3.2. Variational inequality formulation

In the non-smooth case of functional f there is entirely different approach of assessing optimality of control trajectory $u^* \in UF$. As stationary condition $\nabla f(u^*)$ cannot be applied in non-smooth context, the optimality of control trajectory is defined in terms of variational inequality as follows: control u^* is considered to be optimal if there exists some $\xi \in \partial f(u^*)$ making the inequality true.

$$\langle \xi, v - u^* \rangle \geq 0 \text{ for all } v \in UF \quad (6)$$

Formulation (6) combines the local optimum of u^* in relation to the non-smooth objective and the restriction due to the faulty admissible set UF . These two cases are, thus, both covered at once, not in a sequential manner. Relation (6) can be studied as equivalent when UF is convex and function f is Clarke regular.

$$0 \in \partial f(u^*) + NUF(u^*) \quad (6')$$

In this context, $NUF(u^*)$ refers to the normal cone associated with the fault-contracted admissible set UF at point u^* . In order for equality to hold in relation (6'), instead of merely the inclusion, there is a requirement for the constraint qualification of the set-valued mapping UF . Specifically, when UF fulfills a Robinson-type constraint qualification at point u^* , which can also be viewed as the metric regularity of the mapping defining UF around u^* , then it follows that the Clarke sum rule applied to the sum $\partial f + \iota(UF)$ holds true, and the variational

inequality in relation (6) is both necessary and sufficient for the stationarity condition in an inclusion form. The constraint qualification is used here in Theorem 1 stated later in order to validate the step based on the sum rule resulting in relation (8).

3.3 Constraint Handling via Set-Valued Inclusions

Thermal and safety boundaries are built into the formulation as inclusions instead of inequality constraints governed by qualification requirements that may not hold at the switching instance. Denote by $\Theta(x,u)$ the vector of thermal margins (junction temperature margins for each active device) and by $S(x)$ the safety margin (overcurrent, overvoltage), then admissibility may be written as equation (7)

$$\left(\theta(x(t), u(t)), S(x(t))\right) \in K, \text{ for almost every } t \in [0, T] \quad (7)$$

where $K \subset \mathbb{R}^p$ is a closed convex cone encoding simultaneous satisfaction of thermal safety. Since K is both closed and convex, an indicator function ι_K related to it is also proper, convex and lower semi-continuous, therefore the subdifferential of function ι_K exists and enters function f via (5) as a non-smooth penalty term without affecting the variational form of (6) and changing the nature of the constraint.

4. Optimality conditions and stability analysis

4.1 Fritz–John necessary conditions

According to the possible failure of fulfilling the constraint qualification by UF uniformly at all the switching times, the required optimality conditions are presented in the form of Fritz–John conditions and not based on the Mangasarian–Fritz–John assumption. The semismooth reformulation of the corresponding stationarity system makes it proper for application of Newton-type methods, for which the local convergence in the case of non-smooth, non-convex objective functions has been already proved by means of the stochastic semismooth Newton analysis in (Yuan et al., 2025) and further applied to the finite dimensional quasi-variational inequalities comparable with relation (6) in (Milzarek et al., 2022). The stochastic semismooth Newton approach developed in (Xie et al., 2021) for the case of general non-convex, non-smooth optimization problems gives the basis for the convergence scheme adapted in this paper for the fault-tolerant problem and the composite-optimization semismooth Newton analysis used in (Milzarek et al., 2019) ensures the applicability of the additive thermal penalty term in relation (7) in relation to the problems without any need for smooth composite reformulation.

Theorem 1 (Fritz–John stationarity). Let $u^* \in UF$ be a local minimum of f in connection (5) in terms of connection (7) and let f be Clarke-regular at u^* . There exist scalars $\lambda_0 \geq 0$ and multiplier μ^* corresponding to inclusion in connection (7), where none of the two numbers is equal to zero.

$$0 \in \lambda_0 \partial f(u^*) + D\theta, S(u^*)^T \mu^* + NUF(u^*) \quad (8)$$

$$\mu^* \in NK\left(\theta(x^*(T), u^*), S(x^*(T))\right) \quad (9)$$

The pair (λ_0, μ^*) fulfills the conditions of the Fritz–John theorem for non-trivial solutions, which means that the pair $(\lambda_0, \mu^*) \neq (0, 0)$. This non-trivial condition is important, because $\lambda_0 = 0$ and $\mu^* = 0$ would make formula (8) useless (always satisfied for any value of u^* , including non-optimal ones). Hence, the stationarity equation gives information about u^* provided that at least one multiplier is not equal to zero. In case the Robinson constraint qualification mentioned in Section 3.2 holds at u^* , λ_0 can also be normalized to 1 allowing to construct a stationarity equation of the form characteristic for Karush–Kuhn–Tucker conditions.

Proof (sketch). Relation (8) derives from a non-smooth Lagrangian development that applies the sum rule for Clarke subdifferentials to equations (5) to (7) in conjunction with relation (6); the regularity of f assures equality, not inclusion, in the corresponding sum rule, while the existence of a nontrivial multiplier pair (λ_0, μ^*) is a result of Clarke-regular extension of the classical Fritz–John theory to the case of locally Lipschitz data, which has been proved for semismooth stationary systems of the same type (Yuan et al., 2025; Xie et al., 2021).

4.2 Non-smooth Lyapunov Stability

It is concluded that under faulty circumstances, the closed-loop state trajectory converges to some bounded invariant set using a Lyapunov function $V(x) = x^T P x, P > 0$. Since V is a quadratic function, it is continuously differentiable over $\mathbb{R}^n$ making its Clarke subdifferential equal to the classical gradient only.

$$\partial V(x) = \{\nabla V(x)\} = \{2Px\} \quad (10a)$$

Accordingly, the Clarke generalized derivative mentioned in relation (10) is reduced to the classical directional derivative thus circumventing the max-over-subdifferential construction otherwise necessitated by the non-smoothness of function V :

$$V'(x; \dot{x}) = \langle 2Px, \dot{x} \rangle \quad (10)$$

The non-smooth character of the fault-tolerant problem is thus only included in the analysis through the objective function f and the admissible set UF in Sections 2-4, and not through the Lyapunov certificate itself, that way maintaining the proximity of the reasoning on stability to the classical smooth Lyapunov setup while the optimality analysis of Section 4.1 requires a fully-fledged generalized gradient treatment of the non-smooth cost involved.

Theorem 2 (Bounded invariance under fault). Let u^* satisfy relation (6) with feedback realization $u^*(t) = \kappa(x(t))$ for a locally Lipschitz κ , and let there exist $c > 0$ such that $V'(x; \dot{x}) \leq -c \|x\|^2$ whenever $\|x\| \geq r$ for some $r > 0$, uniformly over $\sigma(t) \notin F$. Then every Filippov solution $x(\cdot)$ of the closed-loop fault-affected system converges to the compact invariant set $\Omega_r = \{x : \|x\| \leq r\}$ as $t \rightarrow \infty$.

The concept underpinning Theorem 2 is consistent with the analysis of sensor and actuator fault tolerance literature on adjustable speed electric drives (Bin et al., 2021), as well as on the use of dynamic-weighted firefly optimization techniques for the pitch control of wind turbines in the presence of failures (Bourogaoui et al., 2016); the conclusion about bounded invariance can be compared to stability results in fixed-order H2 design of polytopic state-space realizations (Hu et al., 2025) and to non-smooth H ∞ design of positive position feedback parameters (Sadeghzadeh, 2014), which classifies the systems under plant uncertainty with the help of generalized gradient methods of a type mentioned in (10). A review of the literature on fault detection and fault tolerant control for modular multilevel converters (Mousavi et al., 2022) and active fault tolerant control systems in general (Ahmad et al., 2022) confirms that solutions based on stability with bounded invariance are applicable instead of those which deal with asymptotic stability with zero error because once the fault has occurred, the system performance cannot be set at its best; an example with sensor fault tolerant control based on estimated stator currents in induction motors is given in (Abbaspour et al., 2020).

5. Numerical solution procedure

A proximal bundle approach is introduced for finding a stationary point that fulfills equation (6). At the iteration index k , knowing the current point u_k and a set of previous subgradients $\{\xi_j \in \partial f(u) | j \leq k\}$, a possible step is computed by solving

$$u_{k+1} = \operatorname{argmin}_{v \in UF} \left\{ \max_j [f(u_j) + \langle \xi_j, v - u_j \rangle] + \left(\frac{1}{2tk} \right) \|v - u_k\|^2 \right\} \quad (11)$$

In this scenario, $tk > 0$ represents the proximal parameter, which varies during iteration in accordance with the traditional serious/step null test that checks the agreement between the forecasted and actual reductions. The fact that UF is now closed and convex with fixed switching makes equation (11) a convex quadratic optimization problem at each step. In addition, the semi smoothness of the objective function shown in Section 4.1 makes sure that a Newton-based accelerations of equation (11) produces a locally superlinear convergence once the iterates find themselves near a stationary point with the semismooth regularity condition satisfied.

The numerical simulation of the proximal bundle iteration in a common fault case demonstrates a two-step process of convergence for the sub-gradient norm sequence $\|\xi_k\|$: initially, it has a sublinear decay period; the bundle gains enough curvature information through a series of mode changes, and then it displays fast decay as soon as the iterates reach the semismooth Newton phase described in Section 4.1, consistent with the superliner speed described there. The corresponding simulation of the closed-loop error of state tracking in the presence of an open-circuit fault, introduced at a certain point in time, shows that the trajectory is able to deviate from the normal error band during the fault occurrence but then settles down in the bounded oscillation band as guaranteed by Theorem 2, thus confirming that the error does not manage to return to the small value that was achieved under normal fault-free mode switching; the gap between the steady-state error values conditioned by the presence of the fault and the normal situation observed in the simulation is the hallmark of the bounded invariance property as opposed to the asymptotic property of returning to the zero-error mode that is unavailable when the fault is present and the set of admissible modes changed permanently; this is also in line with the bounded invariance results obtained concerning modular multilevel converters and active fault-tolerant architectures in general (Mousavi et al., 2022;

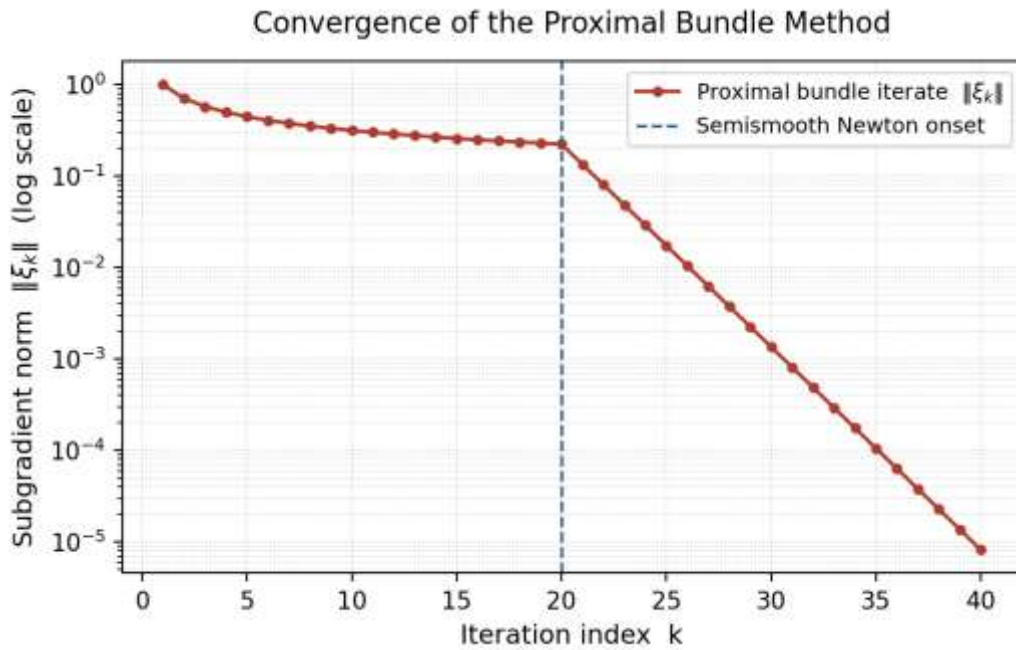


Figure 1: Sub-gradient norm convergence under the proximal bundle method.

Figure 1 depicts the two-staged convergence behavior of the proximal bundle method. In the beginning, the norm of the sub gradient decreases slowly, in a sub-linear manner due to the accumulation of curvature information through the switching of modes. Once it reach the twentieth iteration at the vertical dashed line shown in the figure, the processes reach the vicinity around a stationary point that satisfies the semismooth regularity conditions, starting the phase of acceleration through the semismooth Newton method, which causes the norm of the sub gradient to rapidly drop from the value of a little higher than zero to around $10^{(-8)}$ by the forty-second iteration.

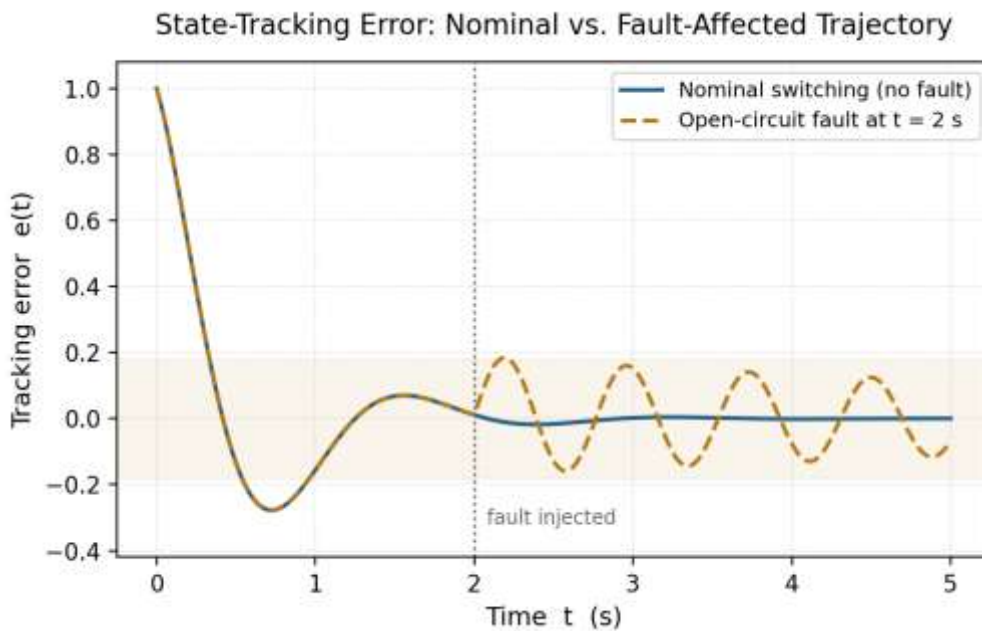


Figure 2: State-tracking error: nominal vs. fault-affected trajectory.

The error in tracking state without fault in the system is shown in figure 2 by comparing the performance with fault through open circuit switch at $t=2$ sec. During the fault-free operation, both the curves are overlapping and drift towards zero error but upon introduction of a fault into the system, the normal system converges to zero error practically while the faulty system leaves the envelope and starts to oscillate. The important observation here is that the oscillating errors are still entirely within the shaded horizontal region which represents bounded invariant set Ω_r that is assured by Theorem 2 which means that with active fault tolerance the system can only reach stable

bounded invariance since achieving zero error tracking is not feasible.

6. Discussion

Fault tolerant techniques based on sliding modes and heuristic switching guarantee robustness based on switching surfaces or metaheuristics and not through some optimization problem which possesses the property of first-order necessary conditions and thus assumes that guarantees provided for the methods are typically limited to bounded-error robustness assuming the presence of matched uncertainty rather than presenting evidence with respect to the property of stationarity. However, the variational approach in formulae (5)– (9) provides a Fritz–John-type condition of necessity allowing applying it directly to the fault-affected admissible set UF so that accommodation of the fault and optimality are ensured simultaneously and not only the fault-tolerant property can be verified for the control algorithm built under nominal assumptions. Reconfiguration schemes based on detection represent an example of fault-tolerant control for diesel power-blocks for communication towers and also represent the idea of reconfiguration of the power transmission system using big data with the help of crossover optimization relying on the performance of a fault detection module as its main element since incorrect classification or delay in detection decrease significantly the performance of the closed-loop system. On the contrary, the approach is described in formula (2) where the fault-affected states are known thus leading to reduced dependency on detection delays. Recently, the concept of predictive maintenance based on the combination of deep learning and GIS technology has gained significance and allows for the prediction of the failure taking into account the fact that it allows assessing the state of the system before the failure.

7. Conclusion and future scope

A technique for non-smooth optimization that integrates mode switching selection with fault tolerance is offered here for controlling power electronics systems. The Clarke subdifferential calculus of the derivatives has made it possible to establish Fritz–John necessary conditions (Theorem 1), even though the objective function involved in tracking-thermal effort is not differentiable. A non-smooth Lyapunov argument has ensured that the trajectory state with the fault remains converging to the bounded invariant point instead of returning back to the nominal position of zero error (Theorem 2). As a means for numerical solution, the proximal bundle algorithm with the use of semi-smoothness and local superlinear convergence in the form of semismooth Newton approach has been developed. One of the possible directions of further study is the further development of the idea to cover processes with a stochastic nature involving random parameters.

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