Model Predictive Control to Alleviate Thermal Overloads

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***Abstract*—An approach inspired by model predictive control is proposed to determine a sequence of control actions aimed at alleviating thermal overloads. The algorithm brings the line currents below their limits in the time interval left by protections while accounting for constraints on control changes at each step. Its closed-loop nature allows to compensate for model inaccuracies.**

***Index Terms*—Emergency control, model predictive control, thermal overload.**

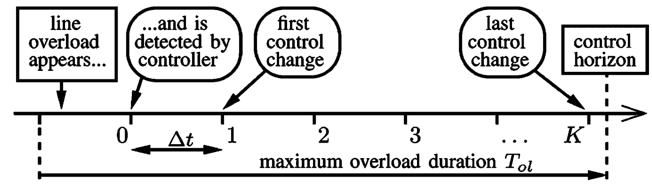

Fig. 1. Sequence of events and controls.

I. Introduction

Some of the recent blackouts involved cascade line trippings due to thermal overloads that were not properly controlled by operators. In such emergency conditions, it is essential to quickly mitigate the consequences of the initial disturbance before protection systems take actions that make the problem more severe [1].

An optimal power flow (OPF) algorithm with proper objective and constraints can be used to determine the best control actions. However, OPF is a purely static and open-loop optimization, which implies some significant limitations.

Time is important in two somewhat contradictory respects. On one hand, there is some time left to alleviate overloads, thanks to thermal inertia. Progress has been made in the real-time estimation of the time left before the conductor material is damaged or the line sag leaves insufficient insulation distance [2]. On the other hand, there are limits on the rate of change of controls [such as phase shifting transformers (PSTs), power produced by thermal plants, etc.]. To account for this, instead of a simultaneous change in all controls, a time sequence of control actions should be determined by solving a multistep optimization problem.

However, this multistep optimization would provide a single "optimal" control sequence for the available system model and the given initial condition. The open-loop nature of this optimization would not allow to compensate for inaccuracies originating from modelling uncertainties, measurement noises, and unexpected reactions of some components. Instead, it is desirable to resort to closed-loop control, relying on the system response in the course of applying corrective actions.

To this purpose, this letter proposes an optimization procedure that bears the spirit of model predictive control (MPC). MPC is a class of algorithms to control the future behavior of a system through the use of an explicit model of the latter [3]. At each control step, the algorithm computes an open-loop sequence of controls optimizing the future behavior and applies the first action of this sequence. Using measurements to update the optimization problem for the next time step introduces feedback. An asset of MPC is the easy handling of constraints. Other potential benefits of MPC in power system control problems have been demonstrated, e.g., in [4]–[6].

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II. Proposed Approach

The objective is to bring the currents in overloaded transmission lines below their admissible values before they are taken out of service by protections. Control actions may involve changing the angle of phase shifting transformers, rescheduling generation, and, in the last resort, shedding load.

A typical control sequence is depicted in Fig. 1, where the controller acts at multiples of a period $\Delta t, T_{\mathrm{ol}}$ is the maximum duration the overload can be tolerated, and K is the number of control steps considered in the first optimization.

Let $\Delta\mathbf{u}^j$ be the n-dimensional vector of control changes at time step $j (j = 1,\dots,K)$. A sequence of K future controls $(\Delta\mathbf{u}^1, \Delta\mathbf{u}^2,\dots,\Delta\mathbf{u}^K)$ is computed as the solution of

$$\min_{\Delta\mathbf{u}^1,\Delta\mathbf{u}^2,\dots,\Delta\mathbf{u}^K} \sum_{j=1}^{K}\sum_{i=1}^{n} c_i \left(\Delta u_i^j\right)^2 \quad (1)$$

subject to

$$\mathbf{p}^j = \mathbf{p}^{j-1} + \mathbf{S}\Delta\mathbf{u}^j \quad j = 1,\dots,K \quad (2)$$
$$\mathbf{u}^j = \mathbf{u}^{j-1} + \Delta\mathbf{u}^j \quad j = 1,\dots,K \quad (3)$$
$$\Delta\mathbf{u}^{\min} \le \Delta\mathbf{u}^j \le \Delta\mathbf{u}^{\max} \quad j = 1,\dots,K \quad (4)$$
$$\mathbf{u}^{\min} \le \mathbf{u}^j \le \mathbf{u}^{\max} \quad j = 1,\dots,K \quad (5)$$
$$-\mathbf{p}_{no}^{\max} \le \mathbf{p}_{no}^j \le \mathbf{p}_{no}^{\max} \quad j = 1,\dots,K \quad (6)$$
$$-\mathbf{p}^{\max} \le \mathbf{p}^K \le \mathbf{p}^{\max} \quad (7)$$

where $\mathbf{p}^j$ is the vector of branch power flows computed at step j, $\mathbf{p}^{\max}$ the corresponding branch power flow limits, $\mathbf{p}_{\mathrm{no}}^j$ is a subvector of $\mathbf{p}^j$ corresponding to the initially non-overloaded lines, $\mathbf{S}$ is the sensitivity matrix of branch power flows to controls, $\mathbf{u}^j$ is the predicted control vector at step j, with the corresponding bounds $\mathbf{u}^{\min}$ and $\mathbf{u}^{\max}$, and c_i is the cost associated with control change Δu_i.

The dc approximation of power flow equations is used here for simplicity, but more accurate sensitivities can be considered. The $\mathbf{S}$ matrix is easily derived from the dc load flow Jacobian and is updated after a topology change.

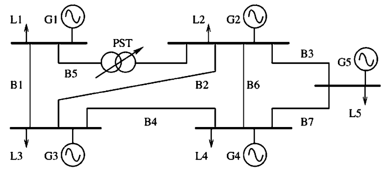

Fig. 2. System used in illustrative example.

TABLE I
AVAILABLE CONTROLS AND RELATED PARAMETERS

control	c_i	Δu^{min}	Δu^{max}
PST	1	- 1 deg.	1 deg.
gener. G1 and G5	10	- 2 pu	2 pu
load L3	100	0	2 pu

Equation (2) is used to predict the future values of power flows. The bounds in (4) take into account the maximum rate of change of each control over a time interval Δt. The optional inequality (6) is used to prevent lines that are initially within their limits from getting temporarily overloaded by the controller. Last but not least, (7) expresses that all power flows have to be within their limits at the end of the control interval (this provides grounds for stability guarantee [3]).

Other objectives than (1) can be thought of, for instance

$$\min_{\Delta\mathbf{u}^1,\Delta\mathbf{u}^2,\ldots,\Delta\mathbf{u}^K} \sum_{j=1}^{K}\sum_{i=1}^{n} d_i^j c_i \left|\Delta u_i^j\right| \qquad (8)$$

where d_i^j is a discount factor [1]. The quadratic objective (1) has the advantage of evenly distributing control changes over the time window.

According to MPC principle [3], only the first element $\Delta\mathbf{u}^1$ of the so computed sequence is applied, at time $j = 1$. At each time step, new power flow measurements are collected and a new control sequence is computed, accounting for changes that have taken place in the system. Obviously, the controller does not act as long as no line is overloaded.

An important feature of the proposed algorithm is the possibility of dynamically updating the value of T_{ol} and hence the number K of control steps (see Fig. 1). Indeed, as the controller starts alleviating line overloads, more time may be available before the lines trip. The horizon is receding, allowing to replace fast but expensive controls by slower but cheaper ones.

III. ILLUSTRATIVE EXAMPLE

An illustrative example is presented on the academic system shown in Fig. 2. Due to some disturbance, lines B1 and B6 get overloaded at time $t = 2$ s. This is first noticed by the controller at time $t = 5$ s, which corresponds to $j = 0$. A fixed overload duration $T_{\mathrm{ol}} = 60$ s is assumed, requiring the overloads to be eliminated in at most $K = 10$ steps. This is a stringent test in which the control horizon is not receding. Thus, K decreases from 10 to 1 with the successive time steps.

The controls, costs, and bounds are given in Table I.

To check the scheme in the presence of modelling errors, the $\mathbf{S}$ matrix used by the controller was obtained by adding noise to the one used to determine the system response.

The evolution of line flows and control changes are shown in Figs. 3 and 4. The initially overloaded lines B1 and B6 are relieved, while the other lines are kept within limits; the latter are all equal to 3.5 p.u. and shown with dash-dotted horizontal lines. Load shedding is used because the problem cannot be solved with the sole help of PST and generators. More generator changes cannot take place because it would lead to overloading line B7. If the model was exact, the control changes would be equally distributed over the control time window. In the shown case, generator rescheduling and load shedding decrease with time because the controller senses that the situation is improving faster than expected initially.

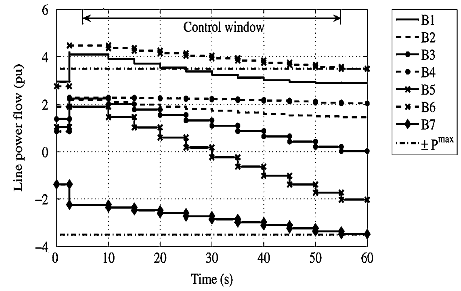

Fig. 3. Evolution of line flows.

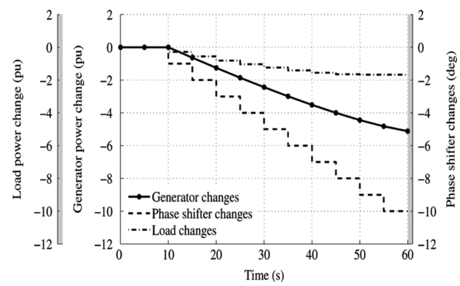

Fig. 4. Control changes.

IV. CONCLUSION

The idea of a closed-loop emergency control of thermal overloads is proposed, in order to bring line currents below their limits before they are tripped. The control horizon can be updated in the course of applying the controls.

Clearly, many additional aspects have to be investigated, such as measurement filtering, infeasibility of the optimization problem, etc. Tests are being performed on a large system to compare various objective functions and assess the capability of the proposed scheme to accommodate modelling errors.

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