

IARIA CONGRESS

Enhanced Robust Convex Relaxation Framework for Optimal Controllability of Certain Large Complex Networked Systems:
An Accelerant Amalgam and Bespoke Numerical Stability Paradigm for a Decoupled and Sequenced Control Strategy on Dense and Homogeneous Temporal Networks

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Presenter Bio

Dr. Steve Chan is an International Academy, Research and Industry Association (IARIA) Fellow. He is the author/co-author of 61 papers, which include 18 IARIA papers and 23 IEEE papers. He has been active in the Network Analysis, Cyber, Artificial Intelligence, and Machine Learning arenas. He remains a dedicated researcher and is always striving to learn.



Table of Contents





Table of Contents:

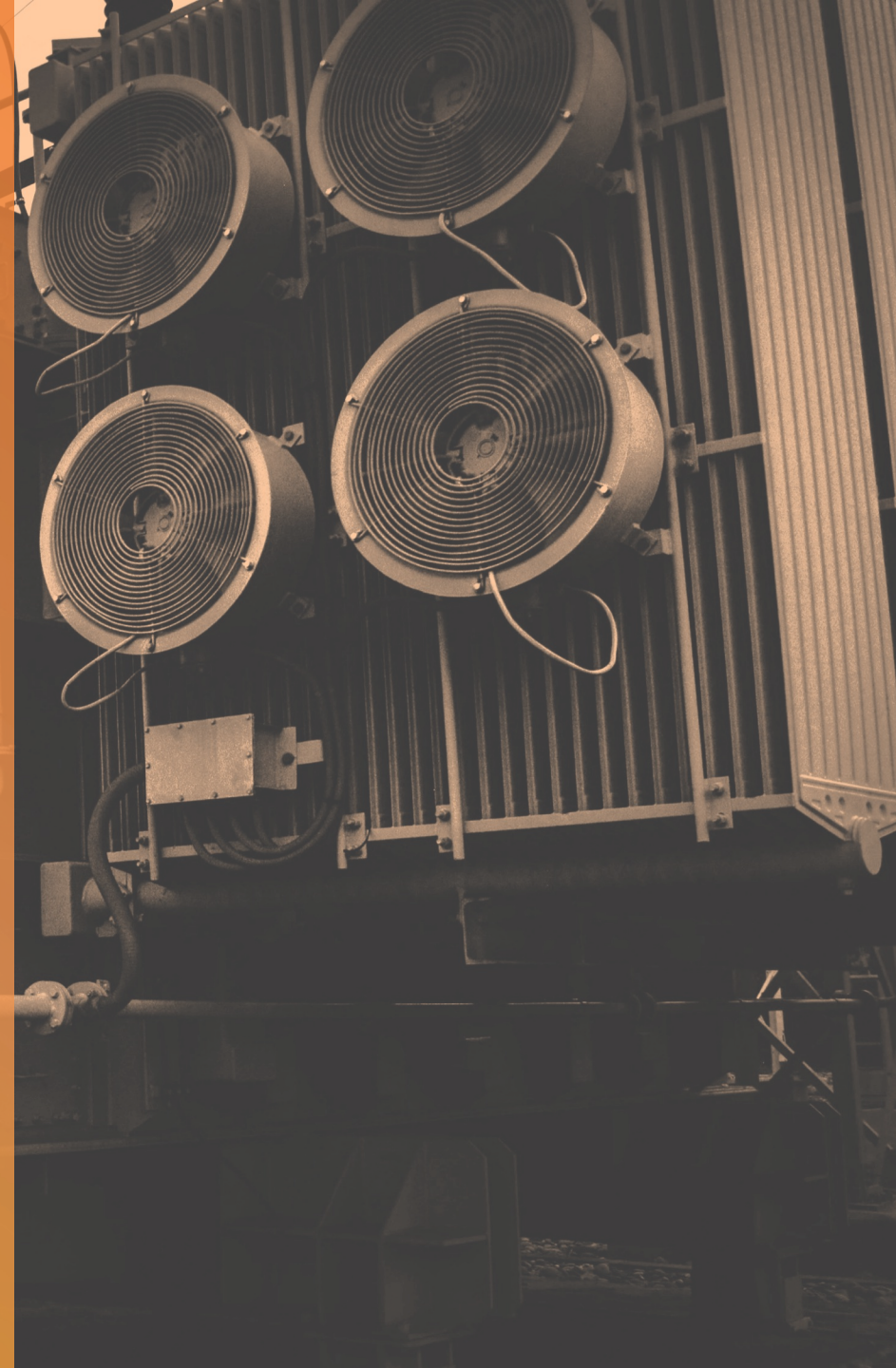
- Introduction.....Slides 4-7
- Background.....Slides 8-18
- Experimentation.....Slides 19-28
- Conclusion.....Slides 29-30

Introduction



Introduction:

Efficient Controllability Problems (ECP) for Large Complex Networked System (LCNS) often involve solving a succession of convex optimization problems, with varied approaches to optimally resolve each problem. In various cases, even when the input set is specifically designed/architected to segue to a convex paradigm, the resultant output set may still turn out to be nonconvex. Further processing is necessary to reach the desired convex paradigm, such as via certain relaxation techniques. However, the involved transformation, during the processing, may result in further nonconvex optimization problems, thereby highlighting the need/opportunity to utilize an Enhanced Robust Convex Relaxation (ERCR) framework.



Introduction cont'd:

In the accompanying paper, we illuminate how leveraging such an ERCR framework (to discern the involved LCNS's topological structure) facilitates or prevents the diffusion of control signals and/or augmented control signals, which in turn informs the computations related to an accelerant amalgam and numerical stability paradigm for effectively leveraging a set of control/driver nodes to influence yet another set of control/driver nodes so as to steer the LCNS to a target state, if a decoupled and sequenced control strategy is utilized.

Introduction cont'd:

The numerical stability paradigm employed by the ERCR framework is, potentially, of value-added proposition and shows promise in contending with certain round-off errors, thereby better facilitating the transformation of certain uncontrollable cases into controllable cases, if temporal networks are considered. For those paradigms, wherein the Bak–Tang–Wiesenfeld (BTW) sandpile cascading effect is a potentiality, this facilitation may be quite significant.

Background



Background:

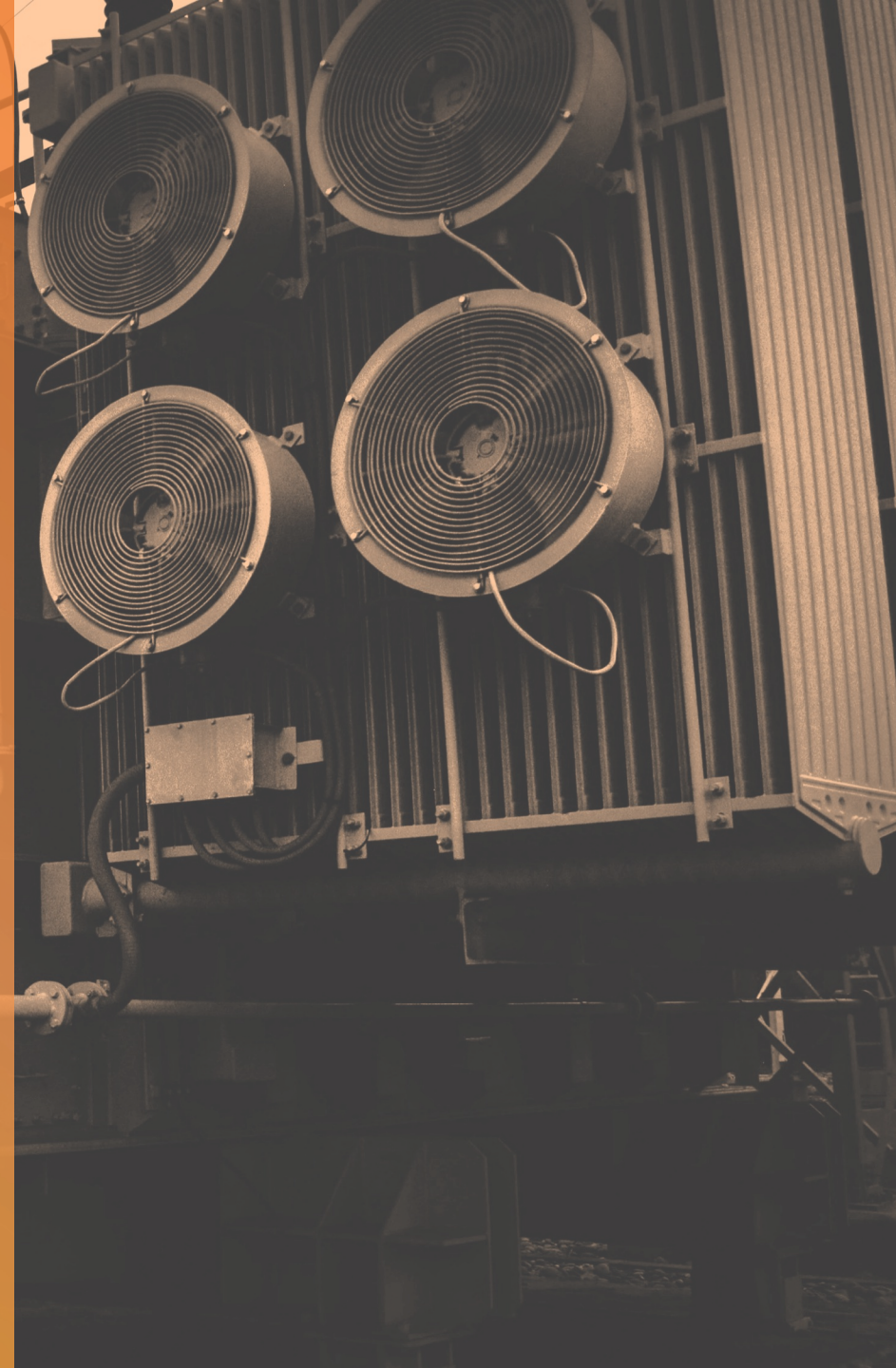
According to control theory, a system is deemed to be controllable, if it can be driven from an initial state to a desired state with apropos specific input(s). It then follows that if certain Target Nodes (TN) of a LCNS can be influenced to move from an initial state vector towards another state vector within a certain period of time, then the LCNS is deemed to be controllable. Mathematical controllability is one matter; actual controllability is entirely another matter.

Background cont'd:

The identification of an optimal set of target control/driver nodes has been the goal of many Complex Network Analysis (CNA) efforts, such as for Supply Chain Vulnerability (SCV) analysis efforts within the realm of Supply Chain Risk Management (SCRM). Yet, these SCRM efforts have become quite complicated, as physical systems and information systems are increasingly being fused into Cyber-Physical Systems (CPS), wherein it is possible to control physical systems, via cyber systems .

Background cont'd:

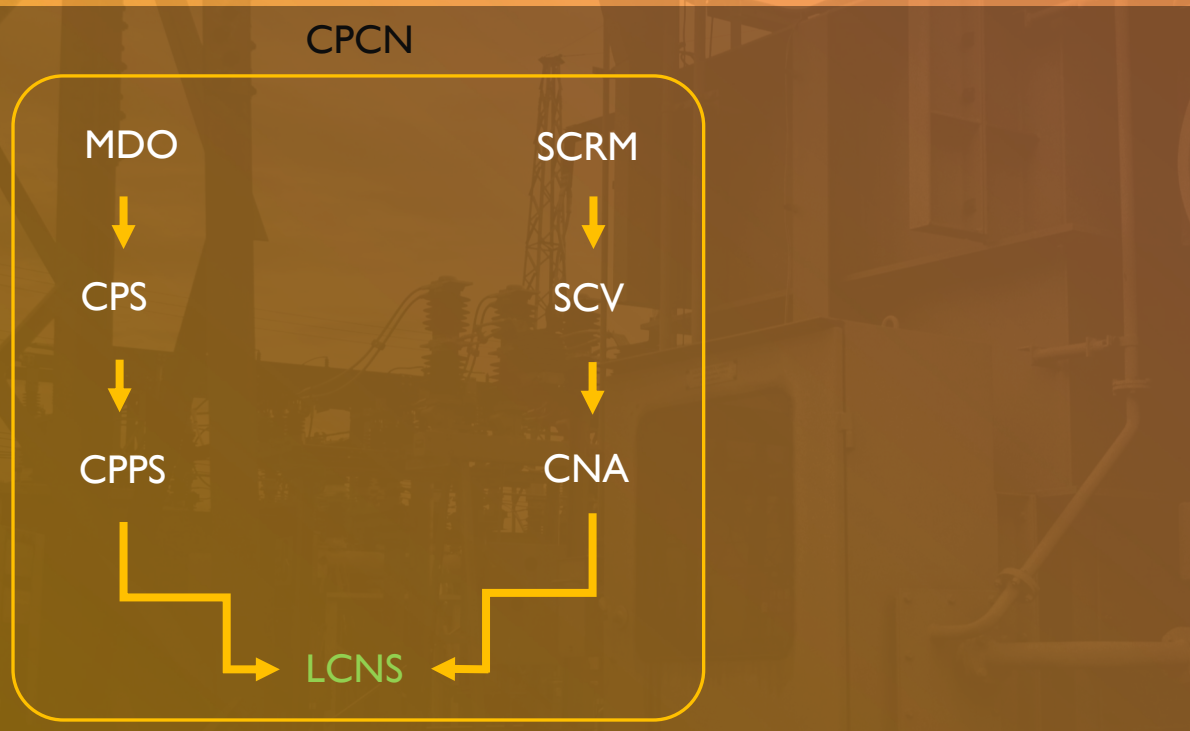
Various works (including the paper associated with this presentation) are examining the realm of minimum Constrained Input Selection (minCIS) problems. Oftentimes, the associated research also endeavors to address Control Signal Energy Cost (CSEC). With these CSEC constraints, the minCIS problem moves to being a minimum Cost Constrained Input Selection (minCCIS) problem. To further complicate matters, it is necessary to consider minCCIS amidst various uncertainties (minCCIS-u). These uncertainties include, among others, time delays; the issue of time delays brings into question whether the ability to operationalize a Control Maneuver (CM), which is comprised of Control Actions (CA), persists beyond the immediate time period and is available when desired.



Background cont'd:

If the involved CAs and/or their overarching CMs are able to influence the intended TN, then the TN are considered to have been subjected to “Targeted Control” (TC). If TC can be achieved, then the paradigm is said to be subject to effective Command and Control (EC2). Slides 13 through 18 delineate TC, via TN, in the described environs of minCCIS-u, while considering the discussed element of time; hence, the involved problems are considered Temporal Problems (TPs) with uncertainty (TPUs).

Cyber-Physical Complex Network (CPCN)



CPCN = Cyber-Physical Complex Network

MDO = Multi-Domain Operations

CPS = Cyber Physical System

CPPS = Cyber Physical Power System

SCRM = Supply Chain Risk Management

SCV = Supply Chain Vulnerability

CNA = Complex Network Analysis

LCNS = Large Complex Networked System

Large Complex Networked System (LCNS)



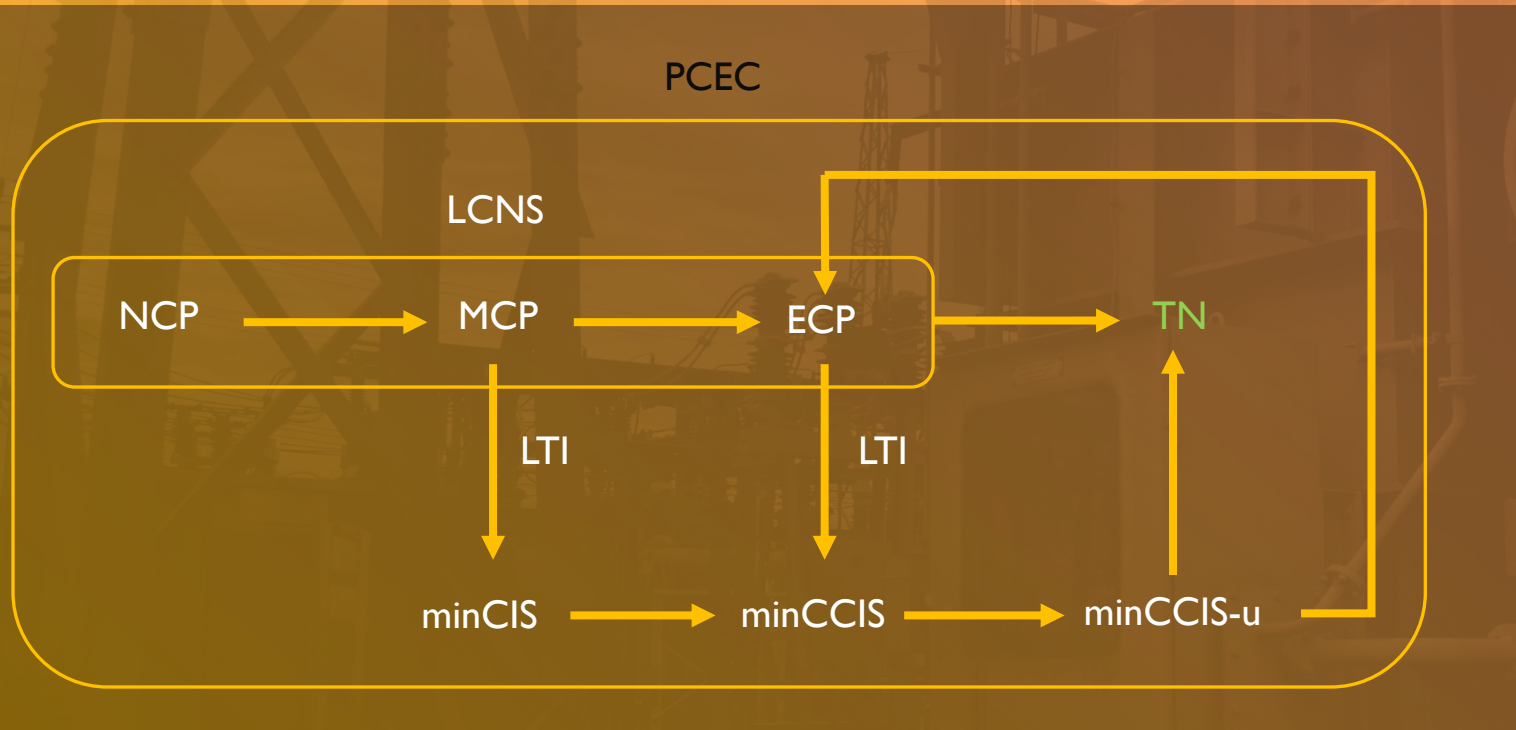
LCNS = Large Complex Networked System

NCP = Network Controllability Problem

MPS = Minimum Controllability Problem

ECP = Efficient Controllability Problem

Pragmatic and Cost-Effective Controllability (PCEC)



PCEC = Pragmatic and Cost-Effective Controllability

LCNS = Large Complex Networked System

NCP = Network Controllability Problem

MPS = Minimum Controllability Problem

ECP = Efficient Controllability Problem

LTI = Linear Time-Invariant Dynamics

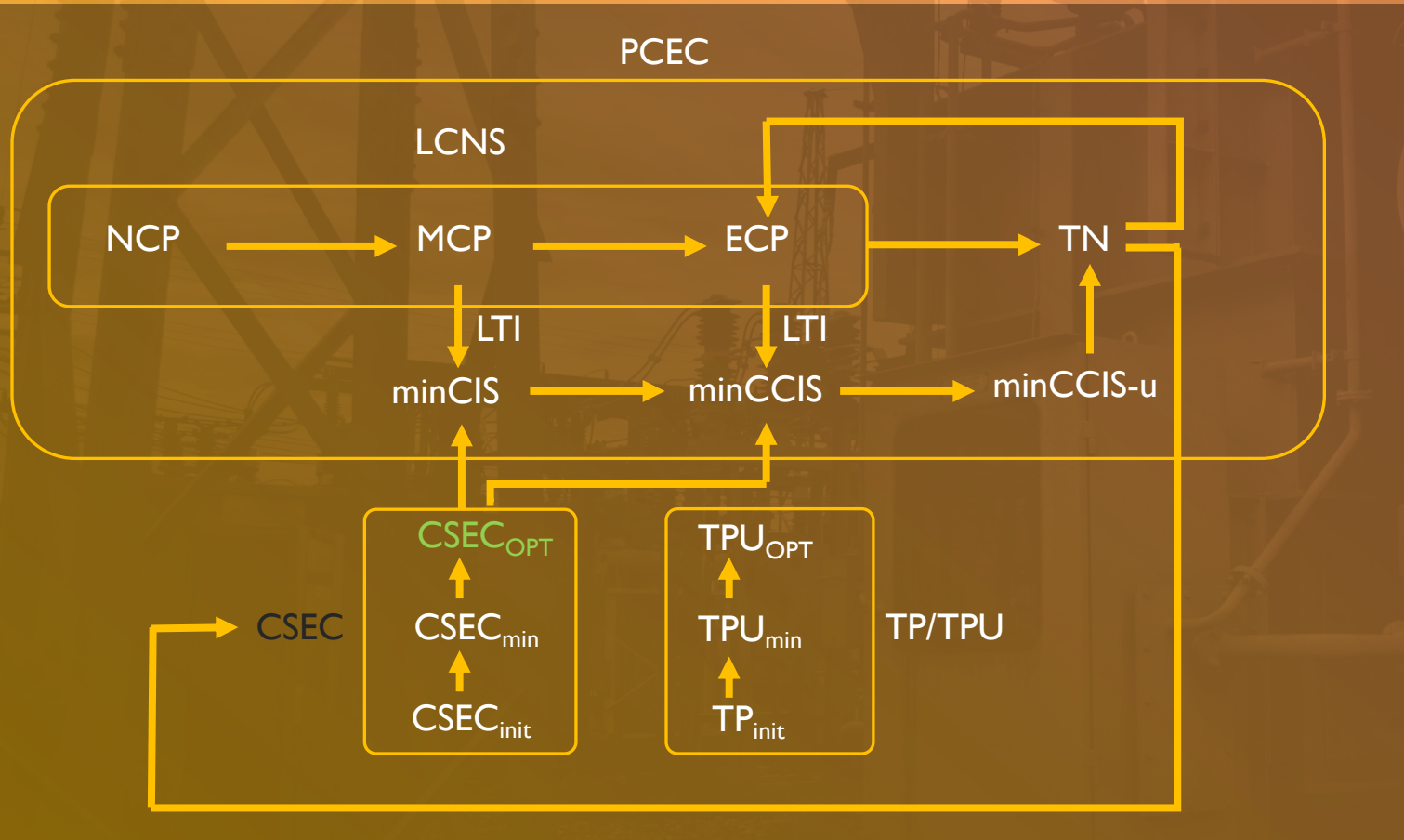
minCIS = minimum Constrained Input Selection

minCCIS = minimum Cost Constrained Input Selection

minCCIS-u = minCCIS amidst uncertainties

TN = Target Nodes

Control Signal Energy Cost (CSEC)



CSEC = Control Signal Energy Cost

PCEC = Pragmatic and Cost-Effective Controllability

LCNS = Large Complex Networked System

NCP = Network Controllability Problem

MPS = Minimum Controllability Problem

ECP = Efficient Controllability Problem

LTI = Linear Time-Invariant Dynamics

minCIS = minimum Constrained Input Selection

minCCIS = minimum Cost Constrained Input Selection

minCCIS-u = minCCIS amidst uncertainties

TN = Target Nodes

TP = Temporal Problem

TPU = TP with uncertainty

TPU_{init} = initial posited CSEC

TPU_{min} = minimum TPU

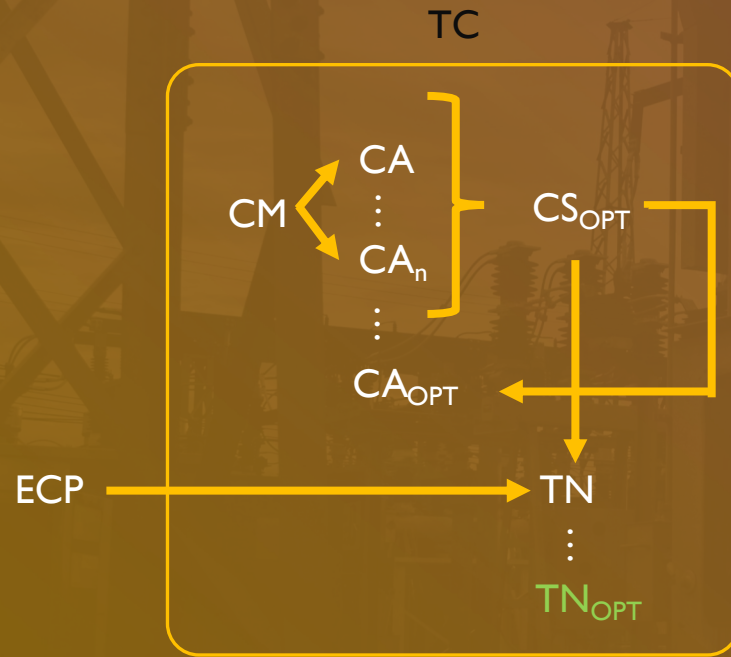
TPU_{OPT} = over an extended period of time

CSEC_{init} = initial posited CSEC

CSEC_{min} = minimum CSEC

CSEC_{OPT} = optimal [and practical] CSEC

Targeted Control (TC)



TC = Targeted Control

CM = Control Manuever

CA_{init} = initial Control Action

CA_n = Control Action n

CA_{OPT} = optimal [and practical]
Control Action(s)

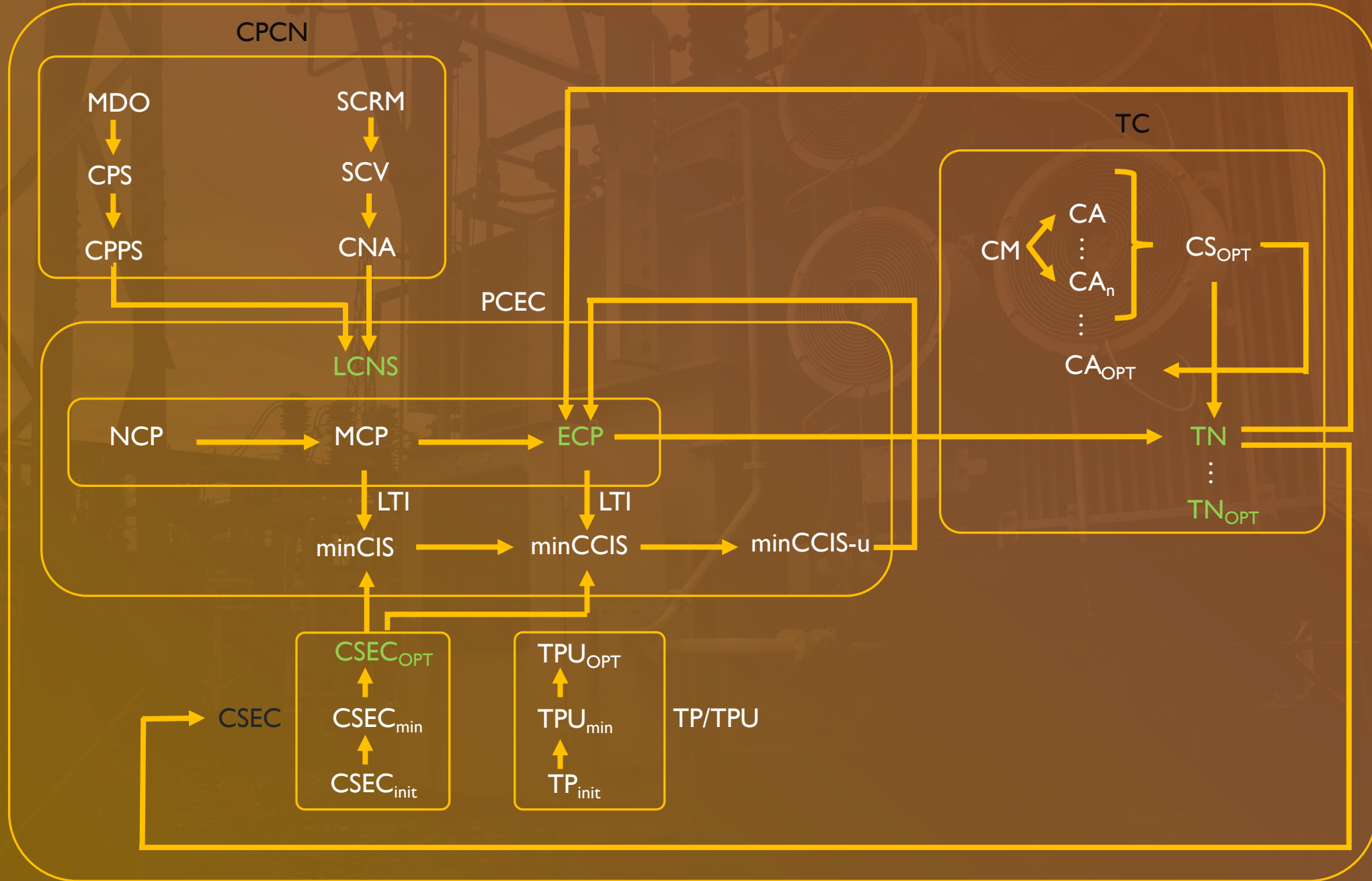
CS_{OPT} = optimal [and practical]
Control Signal(s)

ECP = Efficient Controllability
Problem

TN = Target Nodes

TN_{OPT} = optimal [and practical]
Target Nodes

Effective
Command &
Control
(EC2)

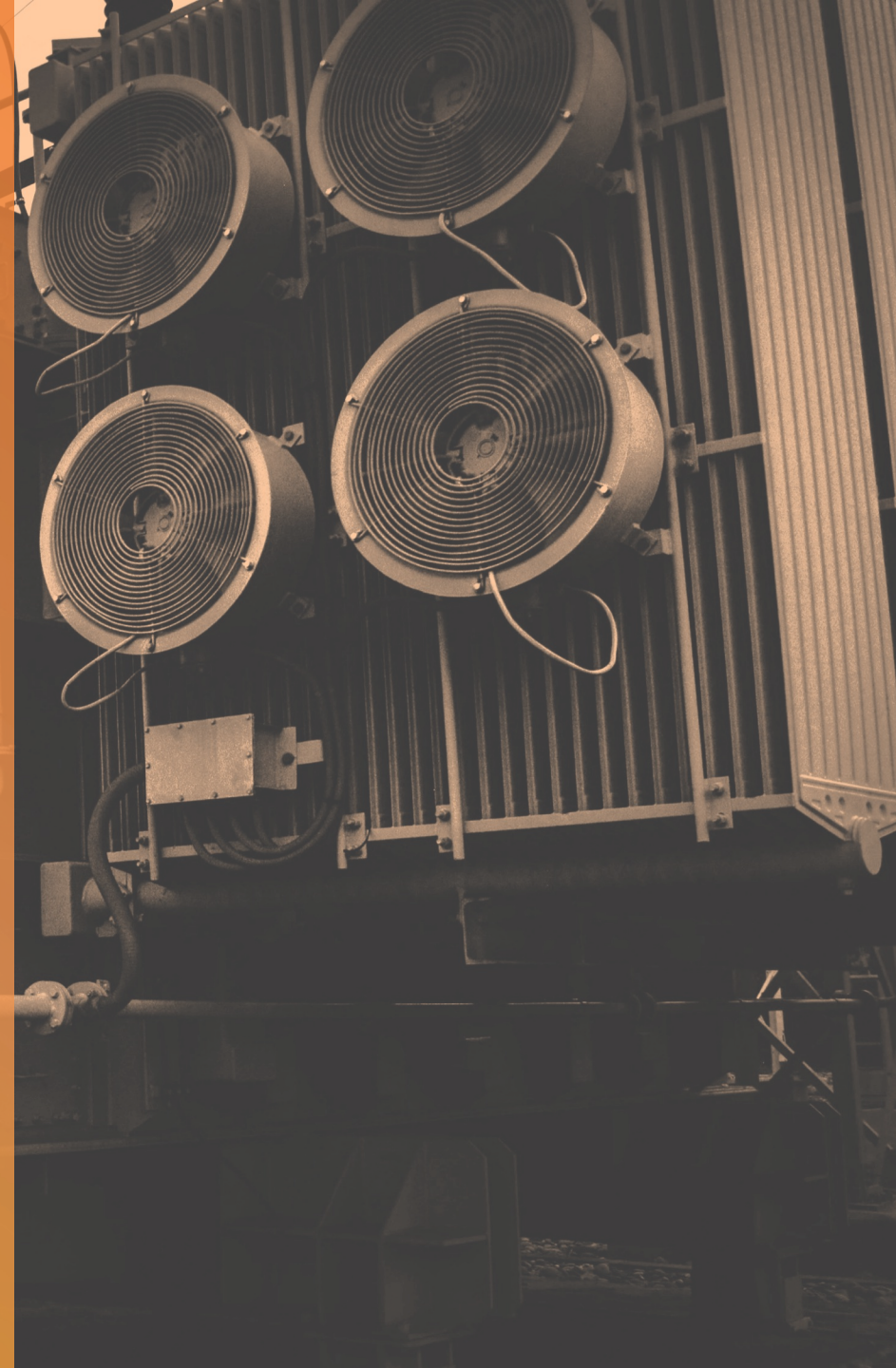


Experimentation



Experimentation:

Three regions were examined: A, B, and C. Of note, B contained certain elements that would impact the supply chain affecting A, B, and C. In many ways, B's criticality surpassed that of A and C, and from a SCV Criticality (SCVC) perspective — for the specific analysis at hand — B was, potentially, the most vulnerable. For this case, the aggregate network of A, B, and C, hereinafter $LCNS_{ABC}$, did not have to be treated in its entirety. The heuristical determination was that an examination of the sub-network of B ($LCNS_B$), would suffice. Hence, it was not necessary to compute the CSEC for $LCNS_{ABC}$ ($CSEC_{ABC}$); computing the CSEC for $LCNS_B$ ($CSEC_B$), would suffice.



Experimentation cont'd:

Also, by simply treating $LCNS_B$, the considered time frame could be further constrained (as contrasted by treating the entirety of $LCNS_{ABC}$); hence, the involved TPU component could be reduced and simplified (TPU_B), and accordingly, the involved CSEC could also be reduced and simplified ($CSEC_B$). The literature review conducted had shown that CSEC could be reduced significantly when the addition of input CS could be accomplished while minimizing the path lengths from control/driver nodes to non-control/driver nodes, via optimal placements of the involved nodes; prior research, delineated in the literature review, had demonstrated that the longest path of the set of involved paths is known as the Longest Control Chain (LCC). As $LCNS_B$ was considered in isolation, as contrasted to considering $LCNS_{ABC}$, it was found that the LCC_B for $LCNS_B \ll LCC_{ABC}$ for $LCNS_{ABC}$; correspondingly, $CSEC_B \ll CSEC_{ABC}$.



Experimentation cont'd:

To further minimize $CSEC_B$ and attain $CSEC_{OPT}$, algorithmic processing was used to ascertain the potentially greatest impact $LCNS_{Bn}$ (a sub-region of $LCNS_B$). In this way, LCC_{Bn} for $LCNS_{Bn} \ll LCC_B$ for $LCNS_B$, $CSEC_{Bn} \ll CSEC_B$, and correspondingly, TN_{Bn} for $CSEC_{Bn} \ll TN_B$ for $CSEC_B$. Selective updating of an optimal Adaptive Impact Vector (AIV_{OPT}) was undertaken for helping derive the potentially greatest impact $LCNS_{Bn}$. In essence, AIV_{Bn} can be derived, via minimizing a recast TN_{Bn} criterion subject to a similarity constraint; the AIV can also be validated, and more finely-tuned, via a decomposition-based evolutionary algorithm coupled with the AIV. The associated constrained paradigm can be transformed into a convex optimization problem, via various Semi-Definite Programming (SDP) algorithms.



Experimentation cont'd:

The significance of deriving $CSEC_{Bn}$, and subsequently, TN_{Bn} , is to have a sufficiently small TN , such that a particular approach, delineated in the literature review, could be used for winnowing to a TN_{Bno} of $LCNS_{Bno}$ (a sub-area of $LCNS_{Bn}$). This winnowing and discernment is necessary, as it provides substantiation that $LCNS_{Bno}$ is logical, that $CSEC_{Bno}$ is reasonable, and that TN_{Bno} makes practical sense.

Experimentation cont'd:

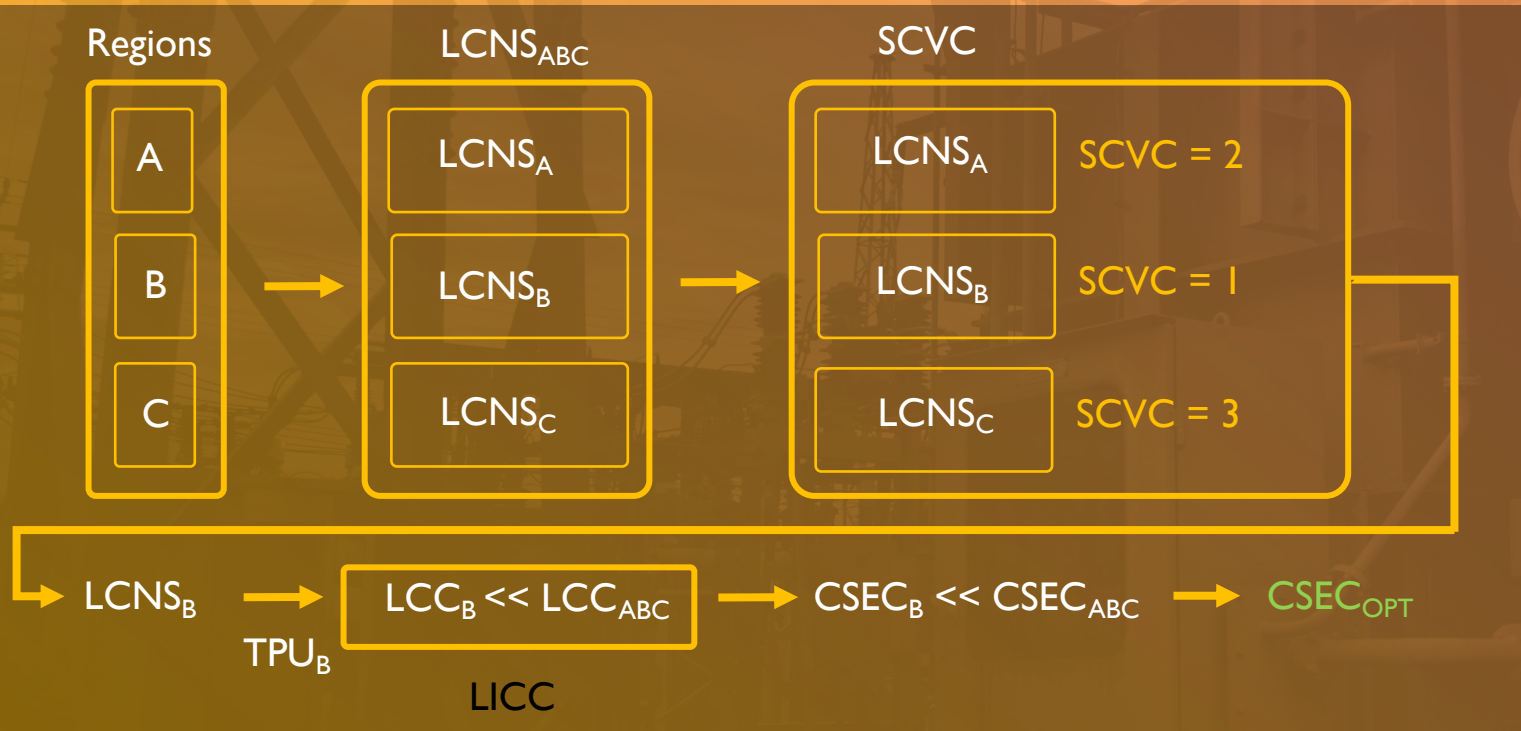
For the involved experimentation, the full node set of $LCNS_{ABC}$ had been heuristically reduced to $LCNS_{Bno}$, its corresponding $CSEC_{Bno}$, and its corresponding TN_{Bno} , which (according to the literature review) might be all that is needed to effectuate the cascading effect of $LCNS_{Bno}$, $LCNS_{Bn}$, $LCNS_B$, and $LCNS_{ABC}$. A TN_{Bnp} accelerant might also serve to assist TN_{Bno} (i.e., $TN_{Bno}-TN_{Bnp}$ Amalgam) in effectuating this paradigm. Ideally, the $TN_{Bno}-TN_{Bnp}$ Amalgam remains optimally small (i.e., TN_{OPT}).

Experimentation cont'd:

The $TN_{Bno}-TN_{Bnp}$ Amalgam (a.k.a., TN_{OPT}) can be revised to include TL_{OPT} for a more accurate amalgam descriptor: $TN_{Bno}-TN_{Bnp}-TL_{OPT}$ or $TN_{OPT}-TL_{OPT}$ Amalgam. The $TN_{Bno}-TN_{Bnp}-TL_{OPT}$ Amalgam need not necessarily effectuate an overarching controlling or cascading effect on $LCNS_B$ and/or $LCNS_{ABC}$; if TN_{Bno} can impact a peer TN (e.g., TN_{Bnn} , TN_{Bnm} , TN_{Bnl} , etc.) or other (e.g., TN_{Bn} , TN_{Bm} , TN_{Bl} , etc.) (i.e., one set of control/driver nodes influencing yet another set of control/driver nodes) so as to steer $LCNS_{Bn}$ and/or other pertinent peer LCNS and/or higher-order LCNS to a target state, then the desired state might be achieved. Slides 26 through 28 show TN_{Bno} , $CSEC_{OPT}$, and the cascading effect for convergence to the desired final state, while the amalgam of TN_{Bno} and TN_{Bnp} (TN_{OPT}) still remains small.



Longest Involved Control Chain (LICC)



LICC = Longest Involved Control Chain

LCNS = Large Complex Networked System

SCVC = Supply Chain Vulnerability Criticality

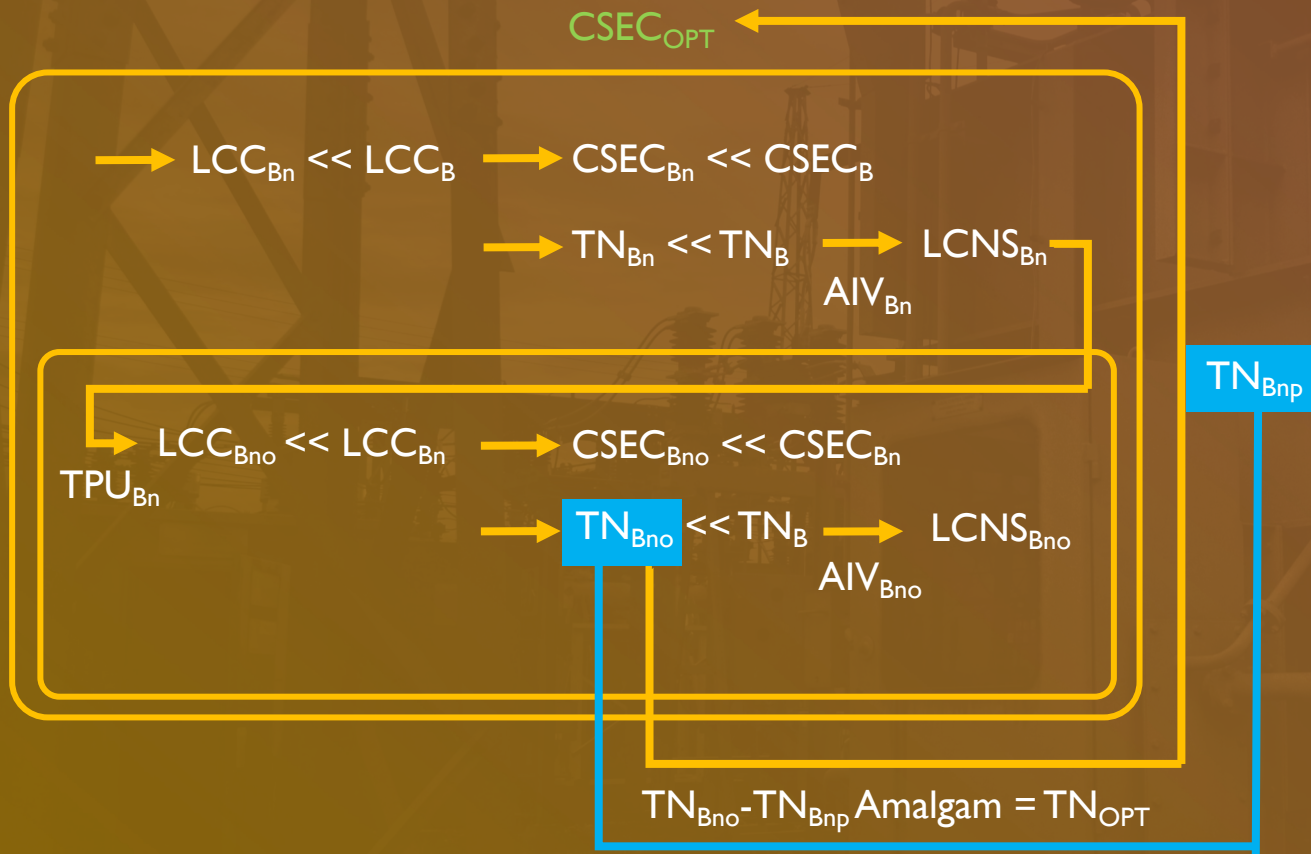
TPU = Temporal Problem with Uncertainty

LCC = Longest Control Chain

CSEC = Control Signal Energy Cost

CSEC_{OPT} = optimal [and practical] CSEC

Longest Involved Control Chain cont'd
(LICC)



LICC = Longest Involved Control Chain

LCC = Longest Control Chain

CSEC = Control Signal Energy Cost

TN = Target Nodes

AIV = Adaptive Impact Vector

LCNS = Large Complex Networked System

$CSEC_{OPT}$ = optimal [and practical] CSEC

Sequence of Involved Transformations (SIT)



SIT = Sequence of Involved Transformations

$CSEC_{OPT}$ = optimal [and practical]
Control Signal Energy Cost

TPU_{OPT} = optimal [and practical]
Temporal Problem with Uncertainty

TN_{OPT} = optimal [and practical]
Target Nodes

TL_{OPT} = optimal [and practical]
Target Links

CS_{OPT} = optimal [and practical]
Control Signal

CA_{OPT} = optimal [and practical]
Control Action

CM = Control Maneuver

Conclusion



Conclusion:

Optimal controllability of certain LCNS involves solving a succession of convex optimization problems. Since further nonconvex problems may be spawned amidst the solving of these convex optimization problems, an ERCR framework is leveraged. The utilized ERCR's bespoke numerical stability paradigm was useful in the facilitation of certain uncontrollable cases into controllable cases, and it was also able to facilitate discerning the involved LCNS's permeability so as to yield the apropos accelerant amalgam for use in the determination of $CSEC_{OPT}$, TPU_{OPT} , TN_{OPT} , TL_{OPT} , among others.

Conclusion cont'd:

The principal submatrices of the Gramian and their inverses were also treated. This helped to inform the involved TC metrics and CS_{OPT} , which in turn informed the derivation of CA_{OPT} and the upstream CM. The involved sequence of transformations contributed to enhancing the actual and accuracy of controllability (i.e., optimal controllability) of the LCNS involved in the preliminary experimentation described in the associated paper. Future work will involve more quantitative experimentation in this area.

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Thank You!

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