CPES-QSM: A Quantitative Method Toward the Secure Operation of Cyber–Physical Energy Systems

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Abstract—Power systems are evolving into cyber–physical energy systems (CPES) mainly due to the integration of modern communication and Internet of Things (IoT) devices. CPES security evaluation is challenging since the physical and cyber layers are often not considered holistically. Existing literature focuses on only optimizing the operation of either the physical or cyber layer while ignoring the interactions between them. This article proposes a metric, the cyber–physical energy system quantitative security metric (CPES-QSM), that quantifies the interaction between the cyber and physical layers across three domains: 1) electrical; 2) cyber-risk; and 3) network topology. A method for incorporating the proposed cyber-metric into operational decisions is also proposed by formulating a cyber-constrained ac optimal power flow (C-ACOPF) that considers the status of all the CPES layers. The C-ACOPF considers the vulnerabilities of physical and cyber networks by incorporating factors such as voltage stability, contingencies, graph theory, and IoT cyber risks, while using a multicriteria decision-making technique. Simulation studies are conducted using standard IEEE test systems to evaluate the effectiveness of the proposed metric and the C-ACOPF formulation.

Index Terms—Cyber metric, cyber–physical energy systems (CPES), cybersecurity, optimal power flow (PF), optimization, power systems.

NOMENCLATURE

General Abbreviations

ACOPF AC optimal power flow.
ACPF AC power flow.
C-ACOPF Cyber-constrained ACOPF.
CPES Cyber–physical energy systems.
CPES-QSM Cyber–physical energy system quantitative security metric.
CPS Cyber–physical systems.
CVSS Common vulnerability scoring system.

Cyber-Constrained ACOPF

\( N \)
Set of buses.
\( R \)
Set of reference buses.
\( G \)
Set of generators.
\( G_i \)
Generator at bus \( i \).
\( L \)
Set of loads.
\( L_i \)
Load at bus \( i \).
\( S \)
Set of shunts.
\( S_i \)
Shunt at bus \( i \).
\( E, E_R \)
Set of branches (forward and reverse).
\( \Re \)
Real part.
\( \Im \)
Imaginary part.
\( v_l^i \)
Voltage lower bounds.
\( v_u^i \)
Voltage upper bounds.
\( P_{g,l}^i \)
Gen. active power lower bounds.
\( P_{g,u}^i \)
Gen. active power upper bounds.
\( Q_{g,l}^i \)
Gen. reactive power lower bounds.
\( Q_{g,u}^i \)
Gen. reactive power upper bounds.
\( S_{d,l}^i \)
Gen. complex power lower bounds.
\( S_{d,u}^i \)
Gen. complex power upper bounds.
\( c_2, c_1, c_0 \)
Gen. cost components.
\( Y_s \)
Load complex power demand.
\( S_i \)
Shunt admittance.
\( Y_c \)
Branch pi-section parameters.
\( s^i_{(i,j)} \)
Complex power flow on line \((i,j)\) upper bounds.
\( p^i_{(i,j)} \)
Current flow on line \((i,j)\) upper bounds.
\( \theta^i_{(i,j)} \)
Branch angle difference lower bounds.
I. INTRODUCTION

The modernization and decentralization of EPS are being facilitated by the integration of DERs and the wide-scale deployment of IoT devices and ICTs. However, this modernization and transformation from old passive EPS to CPES have their disadvantages. Progressively, CPES are becoming more challenging to secure due to the incorporation of IoT/ICT devices that introduce cyber vulnerabilities to physical systems, thus creating attack vectors not previously considered in traditional power system operations [1].

Recent attack incidents, such as BlackEnergy, CrashOverride, and Triton illustrate the growing threat of vulnerabilities in the IoT/ICT infrastructure of power systems [2], [3]. One prominent example of an attack incident affecting the power grid is the 2015 Ukraine cyberattack [4]. In this case, adversaries were able to trip important circuit breakers causing a blackout that affected almost 225,000 customers. Other examples of potential threats to EPS are explored in [5] and [6], where authors demonstrated how attackers can compromise PMUs by spoofing GPS signals via the use of open-source exploitation methods and opensource intelligence (OSINT) techniques.

Even though the electricity sector has matured in the deployment of protection systems, researchers and stakeholders still struggle when quantifying the cybersecurity status and vulnerabilities of systems operating in a CPES [7]. Conventionally, metrics exist to quantify either the cyber or the physical domain independently. For instance, in the cyber domain, IT systems metrics such as the CVSS [8] exist, which only relies on IT experts’ opinions to grade vulnerabilities based on several factors, such as attack vector and attack complexity. While CVSS is useful for analyzing vulnerabilities on several factors, such as attack vector and attack complexity. While CVSS is useful for analyzing vulnerabilities for IT systems, the framework is insufficient when considering critical infrastructure systems. Trying to address these issues, efforts, such as the CERT Resilience Management Model [9], the MITRE’s cyber resilience engineering framework (CREF) [10], and the infrastructure resilience analysis methodology (IRAM) [4], have been proposed but fail to provide sufficiently useful information to system operators due to not having direct interpretations related to the operation of CPES.

While there are metrics that compute individual physical and cyber resiliency factors, there is a lack of metrics designed to study cyber–physical security rigorously in an integrated manner. Also, many of the metrics proposed in the literature are an aggregation of existing metrics, which need domain specialists to interpret them. That is why authors have focused on addressing this lack of existing metrics by proposing different resiliency metrics and methods specially tailored for small-scale CPES. An example is presented in [11], where Bajpai et al. proposed resiliency metrics that capture the level of preparedness of a distribution system to resist extreme adverse conditions. Vellaithurai et al. [12] proposed a stochastic security-oriented risk management technique devised to estimate cyber–physical security indices tailored to measure the security level of a CPS.

The papers presented in [13] and [14] are the ones that are closer to the idea proposed in this article, since the metrics...
and methods proposed in these papers follow a similar formulation based on a MCDM approach. In these papers, the authors explore the concept of combining different factors, coming from different domains, such as the physical, cyber, and device-management domains, using CI to compute an overall resiliency score of the system. The main differences between our proposed approach and the methods presented in these papers are related to: 1) factors considered (different physical, graph-theory, and cyber factors); 2) individual scoring metric for each node/bus in the CPES (thus improving visibility and HiTL processes); and 3) the utilization of the proposed cyber-metric as a deciding factor to improve not only the resilience but also the overall cyber–physical security state of ACOPF solutions for CPES.

Another major contribution of this article is related to the utilization of the proposed cyber-metric as a factor that directly alters the T-ACOPF solutions of a CPES based on the real-time cybersecurity status of the system and, thus, in a way merging the physical and the cyber domains. A limited number of papers have explored the idea of modifying the ACOPF formulation so that it can integrate the status of the cyber layer of the CPES. One example is this article presented in [15], where Huang et al. proposed a cyber-constrained OPF model for the emergency response of smart grids. The proposed model considers both the physical and cyber network by adding cyber-related constraints to the T-ACOPF but has the disadvantage of being a “black-and-white” mapping process that assumes the total loss of control of a physical bus mapped to a “cyber-blind” cyber node (cyber-blind meaning a cyber node that becomes invisible due to failing). Another similar paper is the one presented in [16], where Valinejad and Mili developed a multiagent-based algorithm designed to optimize the power flow (PF) of a CPES based on PF constraints derived from “community resilience” factors, such as levels of emotion, empathy, cooperation, and physical health of consumers. The community and cyber-layer factors are measured based on social media sentiment analysis and other social and human factors related to cognitive science and psychology.

A. Contributions

Contrasting from the papers examined, this article aims to address the specific problem of quantitatively measuring the real-time cyber–physical security of a CPES considering factors that affect both its physical and cyber domains by proposing a novel cyber-metric. It intends to provide an intuitive and easy-to-understand metric that can be used for HiTL operations and can directly reflect the cyber–physical status of the CPES into the ACOPF solutions so that the optimization can be performed not only based on the physical status of the system but considering its current cyber status. The contributions of this article can be summarized as follows.

1) A quantitative cyber–physical security metric for CPES is proposed. The CPES-QSM is designed to quantify the current cyber–physical status of every IoT-connected node in a CPES by combining factors from the electrical, IT, and graph-theory domains using an MCDM approach. The metric provides an easy-to-interpret way to evaluate the current state of the CPES.

2) A C-ACOPF formulation that takes into account not only the physical state of the system but also considers the current status of its cyber domain, using the proposed CPES-QSM as a proxy, is proposed. The formulation is intended to restrict the OPF solution space based on the current cyber status of nodes in the system, which can make them “unreliable” based on vulnerabilities or modeled attack-graphs threats targeting IoT devices deployed in the respective nodes of the CPES.

3) Experimental case studies are investigated using standard IEEE test systems to demonstrate the usefulness of the proposed cyber-metric and validate the utilization of the C-ACOPF formulation for achieving more secure OPF solutions (i.e., considering both the physical and cyber status). The results show how the proposed formulation improves the security and stability of the system when a cyberattack compromises vulnerable nodes.

Fig. 1 depicts the overall framework for the use of the proposed CPES-QSM in conjunction with the C-ACOPF formulation with the objective of reaching a more secure operating state by adjusting the system’s dispatch. The figure illustrates how different factors coming from the cyber, physical, and graph environments are combined into a single quantitative score that is used to improve the system’s operation. The remainder of this article is organized as follows. Section II presents the proposed quantitative cyber–physical security metric, CPES-QSM. Section III focuses on presenting
the proposed C-ACOPF formulation that makes use of the CPES-QSM as a proxy for constraining the optimal solutions based on the cyber factors of the CPES. Section IV presents the experimental setup and case studies performed to evaluate the utility of the proposed cyber-metric and demonstrate its effectiveness for constraining the T-ACOPF. Finally, Section V presents conclusions and future work.

II. CPES-QSM COMPUTATION AND FACTORS

This section presents the proposed quantitative cyber-physical metric, CPES-QSM, that is designed to provide a real-time numerical value to the cyber and physical status of an operating CPES. The CPES-QSM cyber-physical metric provides, via an easy-to-interpret score, operating observability of individual components and/or nodes in a CPES that can be used and interpreted by both human operators and control systems for improving the secure and resilient operation of CPES.

Before the computation of the CPES-QSM is presented, we need to examine the different factors that affect the final computation of the score. Since our focus is toward CPES, the factors considered cover the following three main domains: 1) electrical; 2) IT; and 3) graph theory-based. Within these domains, factors are also classified according to the environment they affect. The environments being considered are: 1) physical; 2) cyber; and 3) network. Each factor, explained in the next sections, has been categorized using one domain and one environment. Additional details about each factor are presented in Table I using a similar format as the one presented by EPRI in [17] and [18]. It is important to note that the cyber-metric framework presented in this article is not tied to the physical environment they affect. The environments being considered are:

A. Electrical Domain Factors

The Electrical Domain factors encompass all factors directly related to the electrical or physical operation of the CPES.

1) Contingency Ranking Performance Index: This factor calculates a contingency PI, using the FDPF 1P1Q contingency ranking method [19], that provides information about the most susceptible lines and buses in a CPES. The specific details for the CRPI factor are shown in Table I. The goal of this factor is to calculate the PI that tells which lines are most susceptible to overload. Note that Target represents the objective value of the factor, i.e., the best value is 0 while the worst is 1 (CRPI values are scaled to the [0-1] range). The process for computing the CRPI is based on the process presented in [19]. A PI value is assigned to each line outage scenario that can occur in a system. The definition of the PI for a contingency outage \( i \) is

\[
\text{PI}_i = \sum_{l \neq i} ^N \left( \frac{P_{i,l}^{\text{flow}}}{P_{i,l}^{\text{max}}} \right)^{2\eta_\text{PI}} \quad \text{for } i = 1, \ldots, N \tag{1}
\]

where \( N \) is the total number of lines in the system, \( P_{i,l}^{\text{flow}} \) is the PF on line \( l \) with line \( i \) out, and \( P_{i,l}^{\text{max}} \) is the maximum power rating for line \( l \). The constant \( \eta_\text{PI} \) is a parameter that allows us to clearly distinguish between overloaded lines and lines with flows within the limit. The use of a large value for \( \eta_\text{PI} \) produces a small PI value (i.e., \( \approx 0 \)) if all line flows are within the limit. On the other hand, if one or more lines are overloaded, the PI value produced will be large. For our test cases, \( \eta_\text{PI} = 2 \) is used. The use of the PI value helps us to quickly determine which lines of the system will have a higher impact when taken out, thus which buses are more important in terms of physical contingency security. Using these PI values, a table for each line in the network can be created and sorted from largest to smallest. The values at the top of the list represent the lines that are most important in the contingency ranking; thus, they are assigned a higher value. The complete process for computing the CRPI value for each bus in the system is shown in Fig. 2.

As seen in Fig. 2, the process for calculating the PI values for each line in the system starts by obtaining the current status of the system via SE, PF, and/or real-time measurements from in-field IoT devices. Then, using these values alongside the defined constants of the process (i.e., MW limits for lines and \( \eta_\text{PI} \)), the loop in charge of computing the PI values for each line in the system is executed. In this loop, line \( l \) is first removed from the network (outage scenario); then...
an FDPF using the 1P1Q method is performed in order to estimate the “new” PFs of the system [19]. The use of the 1P1Q method, instead of a traditional full ACPF, allows the fast execution of a relatively accurate ACPF without the need of an exact result and multiple iterations, thus reducing the computational complexity and allowing its use in both transmission and distribution systems. After the FDPF is performed, the new line flows are computed and used to calculate the corresponding PI value for line $i$ using (1). Finally, the PI value is added to a table or list which will be sorted at the end of the process. After all lines are processed, the final list is sorted from largest to smallest, and the PI value for the line $i_{a,b}$ connecting buses $a$ and $b$ is assigned to buses $a$ and $b$. If a bus is connected to more than one line, the maximum PI of all the lines connected to the bus is selected as the CRPI value for the bus.

2) Voltage Deviation Index: This factor calculates the voltage deviation for each bus in the CPES from the nominal 1.0 pu. Similar to CRPI, VDI is considered to be in the Electrical domain and the Physical environment. The formula to compute the VDI factor is

$$\text{VDI}_k = |1 - \frac{V_{\text{mag, } k}}{V_{\text{nom, } k}}|$$

where $V_{\text{mag, } k}$ is the voltage magnitude measured (in pu) at bus $k$ in the system. The target of the value is 0 since this would mean the bus is exactly at the 1.0 nominal value. This is an easy-to-calculate factor that provides important information related to how far the voltage in a bus is from the nominal 1.0 pu. The specific details for this factor are shown in Table I. The goal of this factor is to calculate the voltage deviation (in pu) of a node/bus.

3) Voltage Collapse Prediction Index: This factor calculates a predicted voltage collapse index, which is designed to determine how close a bus is to voltage collapse. This factor is based on the technique proposed in [20], which is an online technique designed to predict voltage collapse. This factor makes use of voltage magnitudes and voltage angles measured at the respective buses together with the network admittance matrix of the system in order to estimate how close a bus is to voltage collapse when compared to other buses in the system. The method is considered computationally efficient for the real-time prediction of voltage collapse in EPS [20] since it only needs real-time voltage measurements for its computation. The specific details for the VCPI factor are shown in Table I. The goal of this factor is to estimate how close the bus is to voltage collapse and the measurements used are the voltage phasors at sending & receiving buses, and admittance matrix. The VCPI factor for bus $k$ (receiving bus) is calculated with

$$\text{VCPI}_k = \left| 1 - \frac{\sum_{m=1}^{N} V'_{m}}{V_k} \right|$$

where $V_k$ is the voltage measured at bus $k$ and $N$ is the total number of buses in the system. The term $V'_m$ is given by

$$V'_m = \frac{Y_{km}}{\sum_{j=1;j\neq k}^{N} Y_{kj}} V_m$$

where $V_m$ is the voltage phasor at bus $m$ (sending bus), $Y_{km}$ is the admittance between buses $k$ and $m$, and $Y_{kj}$ is the admittance between bus $k$ and $j$. The VCPI factor is computed for each bus in the system.

4) Simplified Voltage Stability Index: This factor calculates an SVSI based on the voltage measurements of the system and load flow results. This factor is based on the indicator presented in [21], and the RED concept detailed in [22]. This factor has a similar, but not equal, objective as the VCPI factor presented previously as it is designed to determine how stable a bus in the system is, in terms of voltage collapse. However, the main difference with VCPI is its ability to estimate the voltage stability of a bus based on the RED to the nearest generation bus. In other words, it uses the difference in voltage between the nearest generation bus and the analyzed bus while comparing them to the maximum voltage change in the system (measured considering the substation as the bus with the maximum voltage value). In essence, the estimation of the voltage stability, using this factor, is directly related to how well the generation resources can modify and adjust the voltage at the respective bus. The inputs to compute this factor are: the voltage phasors (voltage magnitude and angle) from the closest generator ($g$), substation ($m$), and receiving ($k$) buses. The admittance matrix is also needed to find the nearest generator to bus $k$, which, in turn, can be determined using the RED. The details for the SVSI factor are shown in Table I. The SVSI factor for node $k$ can be computed using

$$\text{SVSI}_k = \frac{\Delta V_k}{\beta V_k}$$

where $V_k$ is the voltage phasor at bus $k$, i.e., our analyzed bus, and $\beta$ is a correction factor that computes the highest difference of voltage magnitudes between any two buses in the system (in the equation, buses $m$ and $l$). The term $\beta$ is computed using

$$\beta = 1 - (\max(|V_m| - |V_l|))^2.$$  

Finally, $\Delta V_k$ can be estimated using

$$\Delta V_k \cong |V_g - V_k|$$

where $V_g$ is the voltage phasor of the nearest generator bus (at bus $g$) to bus $k$. This value is computed using the RED concept that indicates the relative distance of each load bus to all the generator buses in the system [22], [23].
B. Graph-Theory Domain Factors

The graph-theory domain factors encompass all factors that are directly related to the topology of the evaluated network. The topology of the overall CPES is assumed so that the physical and cyber networks are isomorphic graphs. This means that each node in the physical layer of the system is mapped one-to-one with a node in the cyber layer of the system [14]. For instance, if we assume that the physical graph of the system, i.e., the power network, is represented by \( G_p \), while the cyber graph, i.e., the cyber network, is represented by \( G_c \), a bijective relationship can be defined as

\[
f : G_p \rightarrow G_c, \ |(x, y)\in G_p \Rightarrow (a, b) \in G_c.
\]

It is important to remark that the assumption of “isomorphism” between the cyber and power networks is only considered when mapping the cyber elements with power systems components. This assumption ensures that each physical (power system) node has a representative “mapped” cyber node, which, in turn, can be composed of various devices such as multiple measurement and control devices. This mapping allows us to include very detailed cyber models, while retaining the overall structure of the system and, thus, lets us determine how a compromised cyber node may directly affect the physical system mapped to it. In other words, isomorphism is only maintained between the primary physical and cyber graphs and minor graphs, composed by multiple devices, can exist inside nodes of these primary graphs. Fig. 3 shows an example of the isomorphic power and cyber graphs. This assumption is not made for the communication topology between devices, in fact, various types of communication topologies, such as star, ring, or point-to-point, can exist without any discrepancies.

Based on the assumptions described above, different graph-theory factors are considered to be included in the computation of the CPES-QSM. These factors are the \( BC \), the \( CC \), and the \( EBC \) of the graph. To calculate these factors, we consider a graph \( G \) composed of \( N \) nodes and \( E \) edges. The order of this graph is given by \( G = (N, E) \).

1) Betweenness Centrality: This factor estimates the importance, i.e., the shortest path BC, of the analyzed node on the overall graph. It quantifies the number of times a particular node acts as a bridge along the shortest path between two other nodes. The BC of a node \( v \) can be calculated as the summation of the fraction of all-pairs shortest paths that pass through \( v \)

\[
BC(v) = \sum_{s\neq t\neq v} \frac{\sigma(s, t|v)}{\sigma(s, t)}
\]

where \( s \), \( t \), and \( v \) are nodes in the set of nodes \( V \). The term \( \sigma(s, t|v) \) is the total number of shortest paths between nodes \( s \) and \( t \), and the term \( \sigma(s, t) \) is the number of those paths that pass through node \( v \). If \( s = t \), then \( \sigma(s, t) = 1 \) and if \( v \in s, t \), then \( \sigma(s, t|v) = 0 \) [24].

2) Closeness Centrality: This factor estimates the mean distance (geodesic path) from a vertex/node \( v \) to every other node. The more “central” a node is, the closer it is to all other nodes, thus, the more important in terms of centrality to the overall graph. The CC of node \( v \) can be calculated as

\[
CC(v) = \frac{n - 1}{\sum_{u=1}^{n-1} d(u, v)}
\]

where \( d(u, v) \) is the shortest path between node \( u \) and \( v \), and \( n \) is the number of nodes that can be reached from node \( v \). A higher value of CC indicates higher centrality [25].

3) Edge Betweenness Centrality: This factor estimates the importance of the edges/lines connected to the analyzed node. The EBC is a factor very similar to BC but calculated for the edges of the graph. The EBC of an edge \( e \) can be calculated as the sum of the fraction of all-pairs shortest paths that pass through the edge \( e \). This can be calculated as

\[
EBC(e) = \sum_{s\neq t\neq v} \frac{\sigma(s, t|e)}{\sigma(s, t)}
\]

where \( s \) and \( t \) are two arbitrary nodes that exist in the set of nodes \( V \). The term \( \sigma(s, t|e) \) is the total number of shortest paths between nodes \( s \) and \( t \), and \( \sigma(s, t) \) is the number of those paths that pass through the edge \( e \). The maximum EBC of all the edges connected to a particular node \( v \) is the EBC value assigned to that node \( v \). Since for our purposes, we are mainly interested in characterizing nodes instead of lines. The details for the BC, CC, and EBC factors are shown in Table I.

C. Cyber Domain Factors

The Cyber Domain factors encompass all factors that are directly related to the cyber-layer structure and operation of the CPES. These factors provide a quantitative way of factoring cybersecurity risks that IoT systems introduce into EPS. The processes followed to calculate the quantitative cyber risk base model (QCR-B) factor or the quantitative cyber risk attack graph-based model (QCR-A) factor are inspired from the cyber risk assessment methodology presented in [26]. The CVSS Version v3.1 (CVSS v3.1) is used as the scoring system that quantifies the cyber risk of the vulnerabilities that exist in the system [27]. Essentially, it estimates the difficulty of vulnerability exploitation for each electronic device that exists in a particular node of the cyber layer of the CPES. The general cyber risk formula used for both QCR-A and QCR-B is \( QCR_{B/A} = P \times I \), where QCR is the risk, \( P \) is the probability, and \( I \) is the impact. The metric values shown in Table II are used to calculate the \( P \) variable according to its corresponding calculation process. More details regarding these metrics are given in [28].
TABLE II
EXPLOITABILITY METRICS IN CVSS V3.1

| CVSS v3.1 | Metric | Abb. | Metric Value | Numerical Value |
|-----------|--------|------|--------------|-----------------|
| Attack Vector AV | Network | 0.85 | |
| | Adjacent network | 0.62 | |
| | Local network | 0.55 | |
| | Physical | 0.7 | |
| Attack Complexity AC | Low | 0.77 | |
| User Interaction UI | None | 0.85 | |
| Required | 0.62 | |
| Privileges Required PR | None | 0.85 | |
| Low | 0.62 if S = Unchanged |
| | 0.68 if S = Changed |
| High | 0.27 if S = Unchanged |
| | 0.50 if S = Changed |

Fig. 4. QCR-B probability and impact.

1) Quantitative Cyber Risk Base Model: This factor estimates the cyber risk of a cyber node based on CVSS v3.1 and the vulnerabilities identified in the device that exists in that particular node. This is designed to be the base model of the QCR factor that should be used at nodes that are composed of only one IoT device or access point. The probability \( P \) in the risk formulation calculation can be computed as

\[
P = AV \times AC \times UI \times PR.
\]  
(12)

The impact \( I \) of the risk formula is computed using the graph-theory factors presented in the previous section times the total bulk impact on the system

\[
I = (BC + CC + EBC) \times P_{g/l}^{68/12}.
\]  
(13)

where \( P_{g/l}^{68/12} \) is the generation or load percentage of the total generation or load in the system. The risk assessment model that describes this calculation process is presented in Fig. 4. As seen in this figure, this factor estimates what is the probability or likelihood a vulnerability is exploited on the cyber–physical assets, thus causing an impact on the system. Nodes with high \( P \) values (very easy to compromise) and generating/consuming a high percentage of power, with respect to the total load in the system (high \( I \) values), are the nodes that are considered more dangerous to the cyber-secure operation of the system.

2) Quantitative Cyber Risk Attack Graph-Based Model: This factor estimates the cyber risk of a cyber node based on CVSS v3.1 and the vulnerabilities identified in multiple IoT devices that exist in that particular node. This is designed to be the model that should be used at nodes that are composed of multiple electronic devices or access points where serial and parallel attack graphs can be modeled. Fig. 5 shows the QCR-A risk assessment process, which differs from the QCR-B process presented previously due to the inclusion of attack graphs that model the path followed by threats that compromise the devices that make up the cyber node.

The probability \( P \) in the risk formulation calculation for this version of the factor needs to consider the attack graph method followed to compromise the vulnerabilities in the corresponding devices. Depending on the movement method of the threat, i.e., serial or parallel, the leading probability \( P \) is calculated differently. The “leading probability” term is defined as the multiplication of all the probabilities leading to the targeted device. The probability \( P \) for a serial movement is calculated by multiplying the leading probabilities with the interim probability at the last device, where the interim probability is defined as the probability of the device calculated from the CVSS scores of the device’s vulnerabilities. The probabilities for a cyber-node with \( n \) devices are calculated as follows:

\[
P_{n}^{\text{leading}} = \prod_{i=1}^{n-1} P_{i}
\]  
(14)

\[
P_{n}^{\text{avg}} = P_{n}^{\text{leading}} \times P_{n}
\]  
(15)

where \( P_{n}^{\text{avg}} \) is the total serial attack-graph probability of a threat that ends up at device \( #n \). \( P_{n}^{\text{leading}} \) is the interim probability of device \( #n \) and \( P_{n}^{\text{leading}} \) is the leading probability for the path ending at device \( #n \). On the other hand, for a parallel movement of the threat, the total parallel attack-graph probability is calculated by multiplying the parallel probabilities of the leading devices as follows:

\[
P_{n}^{\text{leading}} = 1 - \prod_{i=1}^{n-1} (1 - P_{i})
\]  
(16)

\[
P_{n}^{\text{avg}} = P_{n}^{\text{leading}} \times P_{n}.
\]  
(17)

The impact \( I \) of QCR-A can be estimated using the same approach used by the QCR-B factor, i.e., (13). In a real-time application, both of these factors will be mainly affected by the impact \( I \), which changes according to the percentage of generation or load (at the specific time) with respect to the total load in the system. The specific details for these factors are shown in Table I.

D. Cyber–Physical Energy System Quantitative Security Metric Computation

After the required factors are computed, they are combined using an MCDM approach called the CI [29]. The main advantage of using the CI for aggregating the factors is that it allows the aggregation of criteria (i.e., factors), \( x_{n} \), that can have different units, with the objective of providing an overall score. The CI acts as an aggregation function defined with respect to fuzzy measures. A fuzzy measure \( (\nu) \) is defined as a set function that acts on the domain of all possible combinations of a criteria set [30]. In other words, fuzzy measures can be thought of as a function that provides a value to every possible
combination of inputs. The complexity of the set is determined by the $2^n$ subsets that compose it, where $n$ is the number of criteria, i.e., the number of input factors in the aggregation.

Formally, a general fuzzy measure is defined as a set function $\nu: 2^n \rightarrow [0, 1]$, where $\mathfrak{N} = \{x_1, x_2, \ldots, x_n\}$ represents the set that contains all criteria. The function $\nu$ must be monotonic (i.e., $\nu(\mathfrak{A}) \leq \nu(\mathfrak{B})$ whenever $\mathfrak{A} \subset \mathfrak{B}$), and must satisfy $\nu(\emptyset) = 0$ and $\nu(\mathfrak{N}) = 1$, where sets $\mathfrak{A}$ and $\mathfrak{B}$ contain combinations of criteria. Considering that $\mathfrak{A} \subset \mathfrak{B} \subset \mathfrak{N}$, $\nu(\mathfrak{A})$ represents the fuzzy measure or “importance” of the group/substring $\mathfrak{A}$. Fuzzy measures give weights to all possible combinations of criteria, which offers great flexibility when aggregating different types of criteria using the CI for decision-making processes.

The initial weights (i.e., fuzzy measures) for the individual criteria (e.g., $\nu(x_1)$, $\nu(x_2)$, etc.) must be assigned by “experts,” which are in charge of giving importance to the respective individual factors. This “weighting” process can be performed iteratively using an HiTL approach. On the other hand, the fuzzy measures of the sets that combine multiple factors (e.g., $\nu(x_1, x_2)$, $\nu(x_2, x_3)$, etc.) are computed using the interaction index $\lambda$ estimated as

$$\lambda + 1 = n \prod_{i=1}^{n} (1 + \lambda \nu_i), \quad \text{where} \quad -1 \leq \lambda < 0. \quad (18)$$

The interaction index measures the interaction among criteria, i.e., it can be considered as a measurement of the interaction between criteria (factors) in the decision-making process. If $\lambda < 0$, a correlating relationship between the criteria exists. If $\lambda \approx 0$, no relationship between the factors exists, i.e., they contribute independently to the score $[29]$.

Using the calculated interaction index ($\lambda$), the fuzzy measures of sets that combine multiple factors are calculated as

$$\nu(\{x_1, x_2, \ldots, x_n\}) = \frac{1}{\lambda} \prod_{i=1}^{n} (1 + \lambda \nu_i) - 1. \quad (19)$$

Finally, using the calculated fuzzy measures and the values of the factors $x_1, x_2, \ldots, x_n$, the CI can be computed as

$$\text{CI}_i = \frac{n}{n-i+1} \nu(F_i) \quad (20)$$

where $x_0 = 0$ by convention, and $F_i = i, \ldots, n$ is the subset of indices of the $n-i+1$ largest component. The output of the CI usually lies in the unit interval $[0, 1]$; however, other choices can be defined [29]. A simple numerical example of how to compute $\lambda$ and all the fuzzy measures of a set of three criteria (i.e., three factors) is presented as follows.

Let us assume that there exist a set of three criteria $x_1, x_2, x_3$ that we want to combine using the CI. To compute the CI, we must first compute the fuzzy measures using (19) and their corresponding $\lambda$ using (18). To do this, fuzzy measures for the individual inputs $x$ must be assigned. These are assigned as expert weights (i.e., fuzzy measure values) given by experts. So, $\nu_0 = 0$, $\nu_1 = 0.42$, $\nu_2 = 0.5$, and $\nu_3 = 0.62$, where $\nu_0 = \nu(\emptyset)$, $\nu_1 = \nu(x_1)$, $\nu_2 = \nu(x_2)$, and $\nu_3 = \nu(x_3)$. Then, using (18), $\lambda$ can be solved for as $\lambda + 1 = (1 + \lambda \nu_1)(1 + \lambda \nu_2)(1 + \lambda \nu_3)$. For this particular example, $\lambda = -0.748$. Finally, using the calculated $\lambda$, we can use (19) to compute the remaining fuzzy measure values for all the combinations of the set of criteria. The corresponding values calculated for the example given are $\nu(x_1, x_2) = 0.75$, $\nu(x_1, x_3) = 0.82$, $\nu(x_2, x_3) = 0.86$, and $\nu(x_1, x_2, x_3) = 1.0$. With the fuzzy measure (i.e., weights) calculated, the CI can be then computed for any input values $x_1, x_2,$ and $x_3$ using (20).

For our case, the CI is the method used to combine the different Electrical, IT, and Graph-theory factors that characterize the current state of a CPES and, thus, compute the CPES-QSM for each node that exists in the CPES. For instance, the factors used as inputs to the CI that produces the CPES-QSM for node $i$ could be $x_1 = \text{CRPI}_i$, $x_2 = \text{QR-B}_i$, $x_3 = \text{VCS}_i$, $x_4 = \text{SVSI}_i$, and $x_5 = \text{VCPI}_i$. Each one of these factors is given a corresponding importance or expert weight (fuzzy measure) $\nu_1, \nu_2, \ldots, \nu_5$. It is important to note that other papers in the literature, such as [13] and [14], have also used the CI approach for combining different factors in the process of computing cyber–physical resilient analysis metrics, due to the CI characteristics of allowing the aggregation of nonadditive nonlinear criteria without assuming independence of each criterion. More details about the main differences between our proposed approach and works in the literature are specified in Section I.

III. CYBER-CONSTRAINED ACOPF FORMULATION

This section presents an overview of the proposed C-ACOPF formulation. Section III-A focuses on presenting and discussing the T-ACOPF formulation. Section III-B presents the modifications made to the traditional mathematical formulation of the ACOPF so that it can take into account both physical and cyber operating factors of the CPES being optimized; allowing for the consideration of cyber factors in its decision-making process.

A. Traditional ACOPF Full Formulation

The classical ACOPF formulation can be written as presented in (21)–(30). Equation (21) is the objective cost function of the system, (23)–(25) represent the operational power constraints, (26)–(29) represent the branch power and current constraints, and (30) represents the voltage angle difference constraints. There exist other formulations and extensions, such as security-constrained optimal PF, DC OPF, and other relaxations [31], [32], [33], [34]. However, our proposed C-ACOPF is based on the traditional nonconvex ACOPF polar formulation presented

$$\min \sum_{k \in G} c_{2k} (\Re(S_0^k))^2 + c_{1k} (\Re(S_i^k)) + c_{0k} \quad (21)$$

s.t.:

$$\theta_r = 0 \quad \forall r \in R \quad (22)$$

$$S_i^d \leq S_i^g \leq S_i^{gu} \quad \forall k \in G \quad (23)$$

$$v_i^l \leq |V_i| \leq v_i^u \quad \forall i \in N \quad (24)$$

$$\sum_{k \in L_i} S_i^l - \sum_{k \in L_i} S_i^d - \sum_{i \in E_i} (Y_i^s)^* |V_i|^2 = \sum_{(i,j) \in E_i} S_{ij} \quad \forall i \in N \quad (25)$$
\[ S_{ij} = \left( Y_{ij} + Y_{ji}^* \right) \left| V_i \right|^2 - Y_{ij}^* V_i V_j^* \quad \forall (i, j) \in E \]  
\[ S_{ij} = \left( Y_{ij} + Y_{ji}^* \right) \left| V_i \right|^2 - Y_{ij}^* V_i V_j^* \quad \forall (i, j) \in E \]  
\[ \left| S_{ij} \right| \leq \delta_{ij}^0 \quad \forall (i, j) \in E \cup E_R \]  
\[ |S_{ij}| \leq \delta_{ij}^0 \quad \forall (i, j) \in E \cup E_R \]  
\[ \theta_{ij}^L \leq \left( V_i V_j^* \right) \leq \theta_{ij}^H \quad \forall (i, j) \in E. \]  

**B. Cyber-Constrained ACOPF Formulation**

From the formulation presented in the last section, it can be observed how the T-ACOPF formulation essentially prioritizes minimizing a cost function that only takes into account the physical states of the system. However, the C-ACOPF formulation presented in this section is intended to include the cyber–physical perspective of the system. This perspective is facilitated by using the CPES-QSM, presented in the previous section, as a proxy for the cyber–physical factors operating conditions that make up the CPES. The general formulation in (21)–(30) can be stated in a simplified form as

\[
\min C(x) \\
s.t. G(x) = 0 \\
H(x) \leq l \\
\lambda_{\text{min}} \leq x \leq \lambda_{\text{max}}
\]

where \( C(x) \) is the cost function, \( G(x) \) are the equality constraints, and \( H(x) \) are the inequality constraints of the problem. The state variables consist of \( x \) for a particular generation node \( k \). Note that the metric can also be extended to controllable load buses. The CPES-QSM is included in the formulation to bias the optimization solution toward “reliable” generation sources, i.e., the OPF formulation will aim to decrease the power injections from buses where the CPES-QSM value are above a particular threshold. The variable \( \rho \) provides the threshold value for which a bus with a CPES-QSM score above this threshold is considered unreliable. In practice, this value must be determined by expert operators in charge of managing the system being analyzed and may be different for different systems. Considering the partial threshold defined, the CPES-QSM score (CQ) directly impacts the upper bounds of the state variables \( P_k^g \) and \( Q_k^g \) as a scalar multiple. It is important to note that the CQ value/score is computed using (20), i.e., \( \text{CQ}(k) = \text{CI} \). The variables \( \alpha \) and \( \rho \) are defined for the lower and upper bounds of the state variables. The new cyber–physical variables \( \rho, \alpha, \zeta, \) and \( \text{CQ}_k \) are included in the inequality constraints of the simplified ACOPF formulation by expanding (33) as follows:

\[
(1 - \zeta) P_k^g \leq P_k^g \leq \alpha P_k^{gu} \quad \forall k \in G
\]  
\[ (1 - \zeta) Q_k^g \leq Q_k^g \leq \alpha Q_k^{gu} \quad \forall k \in G
\]  
\[ \alpha(\rho, \text{CQ}_k, \zeta) = \begin{cases} 
  \left( \frac{P_k^g}{P_k^{gu}}, 1 \right), & \text{if } \text{CQ}_k \geq \rho \text{ for } \zeta = 1 \\
  0, & \text{if } \text{CQ}_k < \rho \text{ for } \zeta = 1 \\
  1, & \text{if } \text{CQ}_k < \rho \text{ for } \zeta = 0.
\end{cases}
\]

The new lower bounds of the state variables become \((1 - \zeta) P_k^g\) and \((1 - \zeta) Q_k^g\). Similarly, the new upper bounds are \(\alpha P_k^{gu}\) and \(\alpha Q_k^{gu}\). The value of \( \text{CQ}_k \) changes according to the current cyber–physical state of the system and differs according to different types of attacks, e.g., DIAs, DAAs, etc., which directly affect the QCR-A/B factors. The generation limits inequality condition of (23) is modified with (35)–(37), while the other inequality conditions of the problem remain the same. The binary variable \( \zeta \) determines if the generator \( k \) must be disabled or adjusted according to HiTl preferences, e.g., if a generator is considered fully compromised and must be disconnected (\( \zeta = 1 \)) instead of just curtailed (\( \zeta = 0 \)).

As seen in the above formulation, \( \rho \) defines the boundaries, which must be defined by experts operating the system, between a reliable and an unreliable generation node. If the CPES-QSM value (shown here as CQ) is greater than or equal to \( \rho \) then the node is considered unreliable and its generation is either curtailed to a range of its minimum to maximum values or completely turned off. On the other hand, if CQ is lower than \( \rho \) then the node is considered reliable and there is no change in its maximum dispatch capacity. It is important to note that the curtailment of the generators can be defined as a continuous function that curtails generation according to a specific percentage value instead of \( P_k^{gil} \). By constraining the generation in unreliable nodes, the OPF solution provides a more “secure” solution that relies on the generation of more reliable nodes at the cost of more expensive generation that yields a higher traditional cost. The final C-ACOPF solution makes the system more secure in terms of the cyber–physical security of the CPES while sacrificing generation cost.

In terms of complexity, it should be noted that the C-ACOPF problem is unchanged from the original ACOPF, as no new constraints are added. However, the feasible solution space for the optimization solver is reduced based on the newly added cyber–physical variables. The C-ACOPF is still a fully nonlinear nonconvex formulation that is solved using a primal-dual interior-point method.

**IV. EXPERIMENTAL SETUP AND CASE STUDIES**

The code used to run the case studies presented in this section can be found in [35]. The case study presented here is based on the IEEE RTS-24 test system, which is the first part of the IEEE RTS-96 test system presented in [36]. This system has ten generators, one slack bus (bus #12), 17 loads, and 32 transmission lines. The specific loads, lines, and generators capacities/parameters are taken from the case model “case24_ieee_rts.m” available in MATPOWER [37]. For this case study, we assume that every physical node that exists in the electrical transmission network is mapped with a cyber node composed of just one IoT device at the cyber layer of the CPES. This will greatly simplify the cybersecurity model of the system for explanation purposes since only the QCR-B factor will be used to characterize the vulnerabilities on the node; but, for more complex CPES, the QCR-A model can be used to model complex attack graph-based vulnerabilities that exist in multiple IoT devices.

**A. Traditional ACOPF Results**

In order to evaluate the advantages, in terms of the CPES security, of using the proposed C-ACOPF formulation, the solution of the T-ACOPF formulation is used as a baseline.
The T-ACOPF solution is obtained by running the ACOPF PandaPower solver [38], which uses the primal-dual interior-point method implemented using the python interior point solver (PIPS) in the PyPower package. Table III shows the generator dispatch solution for the T-ACOPF formulation. The total cost for the solution is U.S. $49,903.5432. Fig. 6 shows the bus voltages and line congestion of the solution.

### B. Cyber-Constrained ACOPF Using CPES-QSM

In order to compute the C-ACOPF solution for the IEEE RTS-24 test system, we must first calculate the CPES-QSM metric value for each node in the system and “adjust” the corresponding generation and PF of unreliable nodes identified based on the current status of the system. The first step in the process is to select the factors to be considered for this case study and assign the respective expert weights for each one of these factors. The factors selected for this case study are: CRPI, QCR-B, VDI, SVSI, and VCPI. The expert weights, i.e., fuzzy measure values, assigned to each one of these factors are: [0.26, 0.55, 0.61, 0.65, 0.66], respectively. A higher value represents higher individual importance of the factor in the final score computation. These weights were estimated after running multiple test cases and manually evaluating the operating conditions of the test system. Based on the number of factors used, there are 2^5 = 32 total fuzzy measure values that go from ν(∅) = 0.0 to ν({x_1, x_2, x_3, x_4, x_5}) = 1.0. Some of the intermediate values are ν({x_1, x_2}) = 0.669, ν({x_1, x_3}) = 0.714, and, ν({x_1, x_4}) = 0.743. Some of them are not listed due to space limitations, but their calculation is trivial. The corresponding λ computed is λ = −0.983.

Using the λ and fuzzy measure values estimated, we can proceed to evaluate the current status of the operating CPES by calculating the CPES-QSM metric value for each node in the system. It is important to remark that at this point, the weights or fuzzy measure values are set and do not need to be recomputed every time the CPES-QSM metric value is estimated. Hence, for computing the CPES-QSM metric for each node, the current operating measurements for each factor considered are obtained and processed to compute the corresponding CPES-QSM for that specific node. For this case study, an ACOPF is run in order to estimate the current operating measurements for each node, which, in turn, are used to compute each factor considered. It is important to note that in a “real” system, these values are obtained either through IoTs and/or SE. Table IV presents the calculated CPES-QSM values for each node in the system according to the corresponding factors computed. The time execution of the T-ACOPF is 1.1209 s, while the time execution of the entire CPES-QSM value computation and C-ACOPF is 1.3647 s. The specifications of the machine in which the tests were performed are: CPU–AMD 4900HS clocked at 3.00 GHz and 16-GB RAM. Based on the tests conducted, the entire CPES-QSM computation and C-ACOPF process seemed to be 0.82× slower, on average, than the T-ACOPF process.

As seen in Table IV, and using a ρ = 0.2 value (where ρ is the limit given by experts that provides the limit difference between a reliable node and an unreliable node), there are a few nodes that can be categorized as unreliable. This is due to the fact that the estimated CPES-QSM value (i.e., CQ) is higher than the limit given by the ρ = 0.2 and, in turn, some of the factors of these nodes tend to be higher than the rest, making them more susceptible to be targeted by attackers. “Case” T represents the case where the CPES-QSM value is estimated based on the T-ACOPF. Case C represents the case where the CPES-QSM value is estimated after the C-ACOPF is run and adjustments are made based on (35)–(37). It should be noted that the values in the table were cut to two significant figures due to space limitations. Results are normally presented using 5–6 significant figures, so further minor differences can be observed in some cases. For this case study, a DAA-type attack, e.g., Denial-of-Service (DoS), is considered as the threat to the system. The threat model for
the cyberthreat is based on the threat model presented in [1]. This DAA threat has the capability of exploiting the vulnerabilities of the affected node(s) making them unresponsive (by delaying control and measurements) to operating commands. In our specific case, all nodes except bus #15 (the affected node) are considered to have a very “secure” operation based on the QCR-B factor estimated. These are categorized using the following parameters {AV: Local, PR: High, AC: High, UI: Required}, while bus #15 is categorized as unreliable based on {AV: Network, PR: None, AC: Low, UI: None} vulnerabilities exploited by the threat. The results obtained showcase how the cyber factors are taken into consideration when deciding the optimal ACPF of a CPES that is currently under attack from a cyber perspective. Table V shows the generator dispatch solution for the C-ACOPF formulation. The total cost for the solution is U.S. $53,621.1357.

Fig. 6 shows the bus voltages and line congestion of the C-ACOPF solution. As seen in the figure, the OPF solution gets adjusted to take into account the unreliable nature of bus #15 (currently under attack), which, in turn, derives from the high cyber and physical factors. The PFs from bus #15 to bus #13 and from bus #15 to #18 get reduced by ≈ 8%, while the PFs from bus #14 to bus #15 and from bus #16 to bus #15 increase by ≈ 7% and 0.45%, respectively. The corresponding CPES-QSM values of the cyber-constrained solution are shown in the last column of Table IV. As seen, the CQ value for node #15 (affected) decreased from 0.21 to 0.16, putting it below the ρ threshold. These results clearly demonstrate how the C-ACOPF increases the generation from other more reliable sources and takes into account the current status of not only the physical system but the cyber-system components;

thus, producing results that make the system more secure and resilient from the cybersecurity point of view. It is important to note how the CPES-QSM values for nodes #14 and #23 are still over the ρ threshold; however, these cannot be directly adjusted based on the ACPF solution since their criticality is derived from the CRPI factor, which, in turn, is related to the physical topology of the system. This factor can be reduced by performing other control operations that directly change the topology of the system, but these control operations are not in the scope of this article. Future work will focus on exploring other control solutions that can be adjusted based on the CPES-QSM metric.

C. Effects of Cyberattacks in Traditional ACOPF and Cyber-Constrained ACOPF Formulations

In this section, the effects that a cyberattack may have in a system, as the one evaluated in the previous section, are explored. The effects are evaluated by comparing the frequency and voltage effects of the system when a cyberattack compromises a vulnerable node. For this case study, we use the dispatch results from the T-ACOPF and the C-ACOPF in order to examine the different responses these systems would have when a DAA threat (capable of exploiting the vulnerabilities of the affected node(s) by making them unresponsive via the delay of control and measurements) is deployed. More specifically, in this case, the cyber threat compromises the vulnerable generator at the unreliable bus identified by the C-ACOPF formulation, i.e., generator at bus #15, by making it inoperable for 5 s. The threat model of such an attack is similar to existing attacks found in the literature [1], [39]. The time-domain simulation of the IEEE RTS-24 test system used for this analysis is performed using the power system analysis toolbox (PSAT) [40].
the current cyber state in order to improve control and operation decisions that could make the system more secure and stable. In this case study, the C-ACOPF correctly cataloged bus #15 as an unreliable node due to its high QCR-B value and limited its generation output to a minimum. So, when the node got compromised (attacked by an adversary), the system did not suffer much and was able to endure any possible subsequent damage. Since the T-ACOPF solution was not “cyber aware” as the C-ACOPF solution, the system presented a higher variability when the attack happened and a longer attack (e.g., 15+ s) may have caused more substantial damage. The loss of 54.30-MW generation is not the same as the loss of 155 MW generation and this is reflected in the results.

V. CONCLUSION

In this article, a quantitative cyber–physical security metric for CPES and a C-ACOPF formulation were proposed to cope with the security challenges of modern CPES. The CPES-QSM cyber-metric was designed to incorporate diverse types of critical factors affecting the cybersecurity and operation of CPES while providing a quantitative value to the cyber and physical status of the operating CPES. This cyber-metric was integrated, as a proxy, to transform the T-ACOPF formulation into a C-ACOPF formulation designed to produce a more secure operating point that considers vulnerabilities existing in IoT and OT devices deployed in the system’s physical and cyber networks. Experimental case studies, based on a DAA-type of attack and using the IEEE RTS-24 bus system, were presented to show the effectiveness of the proposed CPES cyber-metric. The results of the case study were discussed and evaluated against the T-ACOPF formulation, in terms of cost, line loading percentage, and CPES security.

Based on tests conducted, some of the factors considered when computing the CPES-QSM may have a significant impact in the scalability of the proposed method. Therefore, future work will focus on exploring the scalability of the proposed approach by evaluating its performance in large-scale integrated transmission-distribution systems using tools such as PowerModelsITD.jl. Furthermore, the stability of the CI will be examined for the case when a large number of factors are considered simultaneously.

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