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Kohei Arai *Editor*

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Preface

It is with great pleasure that we introduce the proceedings of the Computing Conference 2024, held on July 11 and 12, 2024. This conference served as a platform for researchers and professionals from around the globe to convene and exchange ideas at the forefront of computing and its diverse applications. The enthusiasm and dedication displayed by participants underscored the significance of this event in fostering collaboration and advancing the field.

We received an overwhelming total of 457 contributions from esteemed scholars and practitioners. These submissions underwent a rigorous double peer-review process, facilitated by experts in their respective domains. After careful evaluation and deliberation, a total of 165 papers were selected for publication in these proceedings.

The diverse array of topics covered in these papers reflects the breadth and depth of contemporary computing research, spanning areas such as artificial intelligence, machine learning, cybersecurity, data science, and beyond. Each paper represents a valuable contribution to the collective knowledge base of the computing community, offering insights, innovations, and solutions to pressing challenges.

We extend our heartfelt gratitude to all authors, reviewers, organizers, and attendees whose efforts and contributions made this conference a resounding success. It is our hope that the insights shared and connections forged during this event will continue to inspire and propel advancements in computing for years to come.

Regards,
Kohei Arai

Contents

Selective Coordination Study in a Renewable Energy-Based Microgrid

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Abstract. The wide integration of renewable energy, such as photovoltaic and wind farms, into microgrids poses severe protection challenges due to the uncertain variations in solar irradiance and wind speed. The unpredictable behavior of renewable energy sources necessitates a more adaptable and optimized regulation of the protection devices such as over-current relays. Therefore, a protected 9-bus microgrid power system is modeled in ETAP based on IEEE standards in the presence of different renewable energy sources. Different power system analysis such as load flow, short circuit, relay coordination are studied in normal and contingency operation of the modeled microgrid. With the aim of improving the robustness of the protection system against weather intermittency, an algorithm is proposed to optimize the coordination between the relays in presence of different renewable energy sources. The performance of the proposed protection scheme has been evaluated for different case scenarios.

Keywords: Microgrid · Renewable energy · Power system protection · Selective coordination

1 Introduction

Renewable energy technologies have seen increasing levels of focus and integration to the power grid in recent years. As this push for integration moves forward the traditional model for power distribution must be changed to reflect the changes in power flow resulting from it. This model of renewable energy can be done to represent a hybrid system utilizing both traditional power production and renewable energy sources to create a realistic model for simulating power distribution and ensuring it is done efficiently, safely, and reliably.

Following the IEEE-9 bus standard a modified variant has been created using the software ETAP [1]. This model will be used to focus on the coordination of the relays within the system to ensure safe operation. This model will focus on Distributed Generation (DGs) with simulated failures and shutdowns of the various components to observe the effects on the coordination of the relays in a variety of conditions [2]. This DG model leads to large fault currents being generated at the point of a given fault, affecting the magnitude and the direction of the short circuit currents. These faults can in turn cause false trips due to the rapid change in current around these failures due to the distribution

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of the generation causing unanticipated changes in the current or causing the tripping of over-current relays. This can cause failure between the primary and secondary relay's coordination, and severely impact the protection coordination of a given grid. Using this concept the 9-bus model is modified to treat DGs in the same manner as traditional generation and test out new relay coordination techniques [3, 4].

New relay coordination techniques must be created due to the increasing prevalence of renewable energy sources, as the existing techniques and protection methodology fall short and must be adjusted to account for the changes in the operation of the systems [4]. These faults in the existing methodology could manifest in being unable to detect a fault within a DG system causing longer lasting failures and possible undetected faults requiring manual shutoff of damaged systems [5]. To address these failings [2] proposes an algorithm to ensure smooth system operation and reliable protection of the system by modifying an existing algorithm.

Another model utilizing under-voltage relays instead of more standard over-current relays suggests that the conditions of a power system utilizing DG would be more optimal [6]. This algorithm addresses that the utilization of a DG system can vary from zero to one hundred percent based on the environmental conditions. To address this issue an adaptive system is proposed that utilizes both over-voltage and under-voltage protection for future research.

Authors in study [7] conduct short circuit analysis using directional over-current relays to model a hybrid power system integrating the renewable energy with a specific focus on solar panels. The paper outlines a technique focusing on comparing the current transformer ratio instead of the current of a fault as it provides a promising detection capability in simulated cases.

Existing literature lacks a detailed study on the operation of a microgrid system, in different contingencies in presence of renewable energy sources (RES). In summary, the new power flow patterns resulting from the uncertainties associated with renewable sources have created the need for a new model for relay systems to ensure the safety and reliability of the power grid. In this paper, an RES-based IEEE 9 bus microgrid is modeled in ETAP to study the operation of the system in normal and contingency conditions.

An improved relay coordination study is required to ensure the robustness of the RES-based microgrid system against different fault currents. Therefore, an algorithm is proposed in this study that runs short circuit analysis in conjunction with selective coordination to determine the optimal operation of the protection system by modifying the relay settings. The specific focus will be on buses connecting to DGs and RESs to ensure the system's reliability in the presence of these variable power generation sources. Hence, a modified IEEE 9 bus system with integration of PV and WTG (Wind Turbine Generator) system is simulated in ETAP for conducting the selective coordination analysis.

The remainder of the paper is formatted as follows: The problem being solved is formulated in Sect. 2. This section also explains some fundamental materials that are used throughout this paper. The proposed algorithm is presented and illustrated through a flowchart in Sect. 3. The modeling of the microgrid based on the IEEE 9-bus system is explained in Sect. 4. Simulation results and analysis are carried out in Sect. 5 to evaluate the effect of the proposed approach on the performance of the protection system. The paper is concluded in Sect. 6.

2 Discussion and Problem Formulation

In this section, the fundamental materials being used, and the problems being solved in this paper are explained.

2.1 Short Circuit Analysis

Short-circuit analysis is a study on an electrical system that determines the magnitude of the currents that flow during an electrical fault. A fault can cause the system to operate in unbalanced conditions. Therefore, unbalanced techniques need to be used in short circuit analysis.

Method of symmetrical components can represent an unbalanced 3-phase power system in terms of three symmetrical networks, i.e. positive (1), negative (2) and zero sequence networks. Each sequence network can be represented with its Thevenin equivalent circuit model seen from the fault location using components' sequence parameters, as shown in Fig. 1. Z's are the Thevenin equivalent impedances and VF is the pre-fault voltage at the fault location.

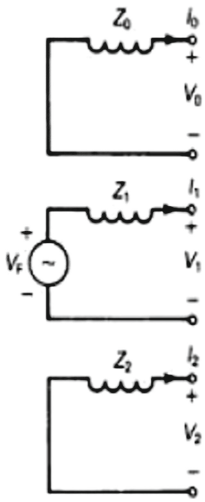

Fig. 1. General sequence models as viewed from fault terminal

Based on the type of fault, the sequence network topology is determined by connecting the sequence Thevenin models and the sequence currents (I_s) are calculated. Then, the unbalanced phase fault currents (I_p) are calculated based on Eq. (1) to Eq. (4).

$$I_p = A \cdot I_s \tag{1}$$

where,

$$I_p = \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix}, \; I_s = \begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} \tag{2}$$

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \tag{3}$$

$$a = 1 \prec 120^o \tag{4}$$

2.2 Overcurrent Protection

An overcurrent relay (OCR), as its name implies, is a device that monitors the current through a device and trips a breaker if the current exceeds a predetermined threshold. Overcurrent relays are used to help protect against electrical faults. Each OCR comes with a time-current characteristic (TCC) curve that defines the operating time of the delay with respect to the available fault current. Based on Fig. 2, overcurrent relays react faster as the available fault current increases with respect to its rated pick-up current.

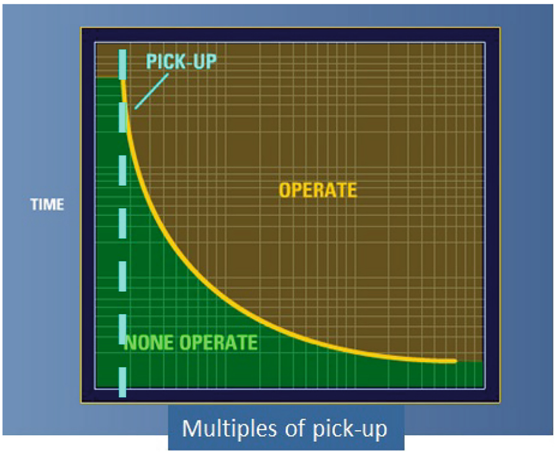

Fig. 2. Time-current characteristic (TCC) curve of an overcurrent relay (OCR)

The inverse time current characteristic of an OCR is expressed as Eq. (5),

$$t(I) = TMS\left\{\left(\frac{k}{\left(\frac{I}{I_s}\right)^{\propto} - 1}\right)\right\} \tag{5}$$

Table 1. TCC characteristic parameters based on IEEE standard [8]

Curve Type	k	α
Moderately inverse	0.14	0.020
Very inverse	13.5	1
Extremely inverse	80	2

where, I is the actual current, I_s is the relay pick-up current setting, k and α are the curve type constants. The latter two parameters are defined based on the available curve types of the OCR, as shown in Table 1.

An OCR is equipped with a current transformer (CT) which reduces the fault current occurred on the protected device. Then the reduced current is measured and used by the OCR to determine the operating time of the interlocked circuit breaker based on Eq. (5).

2.3 Selective Coordination

Selective coordination is carried out to determine the optimum settings for protection devices in the system such as relays, breakers, etc. in order to ensure that proper coordination is achieved. For this purpose, the time coordination curves (TCC) are analyzed to verify the correct coordination between upstream and downstream protection devices including relays.

The main objective of selective coordination study is to isolate the faulty portion as quickly as possible to minimize the severity of damage to the faulted portion and the interruption of un-faulted loads. In other words, a coordination study is carried out in this paper to find the proper settings of protective devices in order to isolate only the faulted portion of the system in a timely manner.

As illustrated in Fig. 3, in case of a fault at the specified location, the closest protective device upstream to the fault location (OCR B) should operate first (primary protection), then the backup protection (OCR A) acts if the primary device does not operate on time. Therefore, the TCC (Time Current Characteristic) curve of the primary device (red curve) should be properly set to be under the backup device's curve (blue curve).

The operating time difference between primary and backup protection for a specific fault is called coordination time interval (CTI) [9, 10]. In a selective coordination study, CTI should be designed to be a minimum of 0.2 to 0.5 s based on different standards for any faulted location. This coordination is illustrated in Fig. 4 and formulated in Eq. (6) and Eq. (7).

$$t_{backup} - t_{primary} \geq CTI \tag{6}$$

$$0.2\,\mathrm{s} \leq CTI \leq 0.5\,\mathrm{s} \tag{7}$$

where, t_{backup} and $t_{primary}$ are the operating times of backup and primary protections, and CTI is the coordination time interval between primary and backup protection for a given fault.

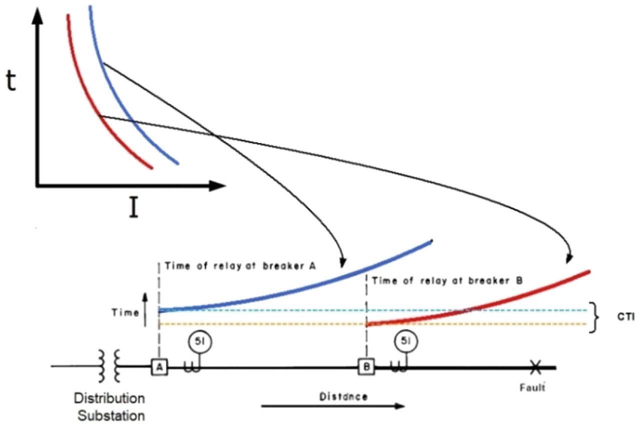

Fig. 3. Relay coordination in a distribution power system

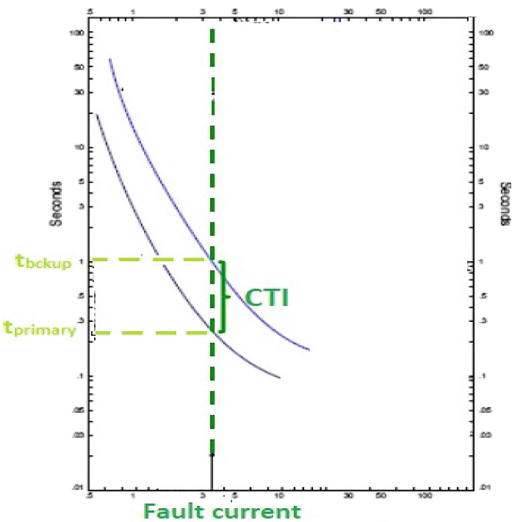

Fig. 4. Coordination time interval between primary and backup protection

For this study we will be attempting to optimize the coordination among the relay's TCC curves in order to minimize the clearing time of faults on different buses connected to RESs, while maintaining the normal operation of un-faulted areas.

3 Methodology

In this paper, a selective coordination study is carried out in a modeled microgrid based on IEEE 9-bus system in the presence of renewable energy sources and distributed generation units. As a result, the settings of the over current relays are optimized to ensure that appropriate protection and coordination is applied in the modeled microgrid. The steps of the algorithm are described below:

Step 1: Perform Load Flow analysis on the modeled microgrid to calculate the power flows and current values at different buses.

Step 2: Perform Short Circuit analysis on the modeled microgrid to calculate fault currents occurred at buses connected to RES or DG.

Step 3: The results of Load Flow and Short Circuit analysis are used to check the CTI between primary and secondary relay with respect to the fault location.

Step 4: If the calculated CTIs are not within acceptable range, relay settings are updated to apply coordination among different overcurrent relays in the modeled microgrid. Then, Steps 3 and 4 are repeated using the adjusted relay settings.

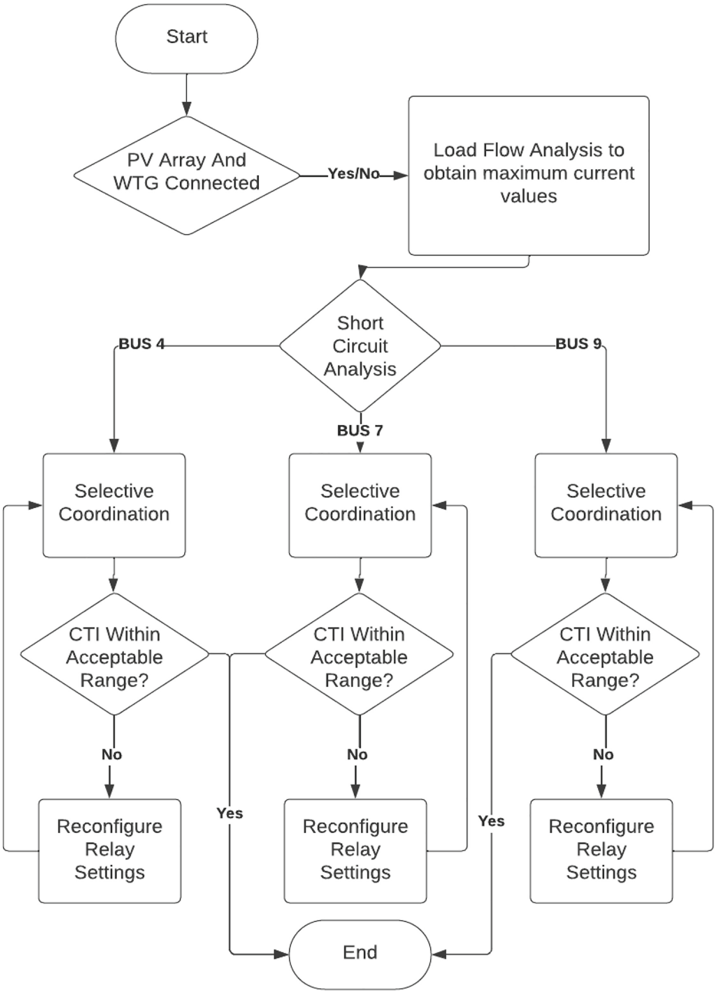

Fig. 5. Selective coordination study flowchart

The flowchart of this algorithm is illustrated in Fig. 5.

4 Model Description

An IEEE 9-bus system is used as the basis of modeling a hybrid microgrid comprising of different distributed generation (DG) units such as diesel engine generators, and renewable energy sources (RES) such as wind turbines and solar panels is modeled in ETAP, as shown in Fig. 6. RESs and DGs are modeled and added to Bus 4, 7, and 9 of the microgrid. Energy storage units are added to RESs to compensate for their production uncertainties during the weather changes and improve the reliability of the power system [1]. The configuration of the protection system is discussed in Sect. 5.

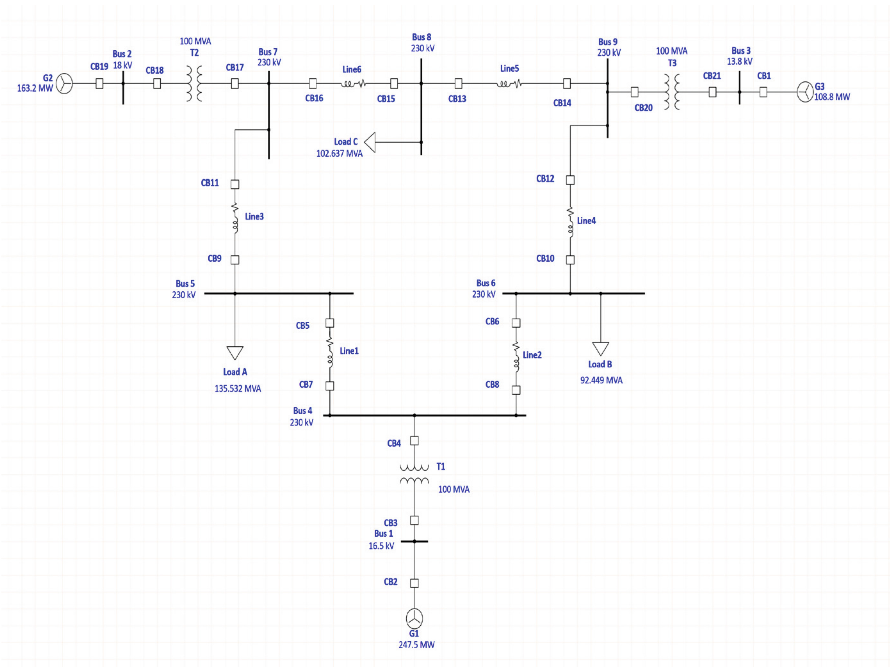

Fig. 6. IEEE standard 9 bus power system

5 Results and Analysis

IEEE 9 bus-based microgrid model discussed in Sect. 4 is used for simulation and analysis purposes in this paper. 28 Overcurrent relays and current transformers (CTs) are sized and located throughout the microgrid to protect various components, such as 3 synchronous generators including a diesel engine generator with rated capacity of 100–170 MW, a wind turbine generator of 163.2 MW, and a 10 MW PV array and 4 different loads [1]. The protected model of the microgrid is shown in Fig. 7.

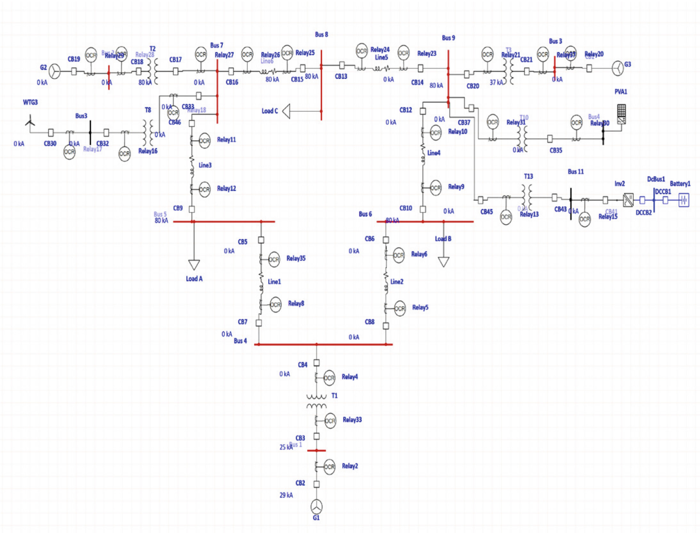

Fig. 7. IEEE standard 9 bus microgrid power system with protection

In order to achieve the objective of the proposed algorithm and implement a well-coordinated protection system, we should use the results of load flow, and short circuit analysis to perform selective coordination in the microgrid system [11].

5.1 Load Flow Analysis

Load flow analysis is carried out in the modeled microgrid using ETAP. The results of the analysis for the generating buses are shown in Tables 2 and 3. It ensures the stability of the microgrid under normal operation with and without the PV systems integration. These values are also used to determine the pickup settings of the protection relays.

Table 2. Load flow results in the modeled microgrid without PV

Bus #	Rated KV	Generated Power Flow		Current In Amp	% Power Factor
		MW	**MVAR**		
Bus1	16.5	139.63	−148.18	540.02	−68.58
Bus2	18	−162.97	−71.01	540.62	91.68
Bus3	16.5	−163.16	144.79	663.39	−74.79
Bus4	230	84.35	−113.50	420.95	−59.65
Bus7	230	−173.83	77.71	566.82	−91.29
Bus9	230	−133.99	10.74	364.31	−99.68

Table 3. Load flow results in the modeled microgrid with PV

Bus #	Rated KV	Generated Power Flow		Current In Amp	% Power Factor
		MW	**MVAR**		
Bus1	16.5	139.63	−148.18	540.02	−68.58
Bus2	18	−162.97	−71.01	540.62	91.68
Bus3	16.5	−163.16	144.79	663.39	−74.79
Bus4	230	58.75	−35.82	186.48	−85.39
Bus7	230	−132.49	72.86	436.73	−87.63
Bus9	230	59.32	−98.46	332.00	−51.61

5.2 Short Circuit Analysis

The results of short circuit analysis are used to set the pickup ratings of the over current relays to ensure protection against maximum fault current available on different buses and components in the power system. The amount of fault currents at each bus is also calculated to apply selective coordination among different relays in the next step. The results for buses connected to RES or DG (bus 4, 7, and 9) are shown in Tables 4 and 5.

Table 4. Short circuit results in the modeled microgrid without PV

Peak Current (kA)	3 phase	L-G	L-L	L-L-G
Bus4	5.28	5.28	5.12	5.73
Bus7	2.66	2.66	6.54	6.52
Bus9	2.48	2.48	5.29	5.36

Table 5. Short circuit results in the modeled microgrid with PV

Peak Current (kA)	3 phase	L-G	L-L	L-L-G
Bus4	5.94	5.28	5.12	5.71
Bus7	7.63	2.66	6.52	6.50
Bus9	6.14	2.44	4.96	4.99

5.3 Selective Coordination Analysis

Relays pickup settings are adjusted based on the results of short circuit analysis to ensure that all components are protected against over current situations throughout the modeled microgrid. ETAP Star tool is used to implement the selective coordination method introduced in Sect. 3. Different settings related to the Time Current Curve (TCC) of the overcurrent relays are optimized based on the proposed algorithm to achieve suitable coordination among the protective devices in case of maximum fault at different buses in the modeled microgrid. TCC coordination for the relays protecting buses connected to RES or DG (bus 4, 7, and 9) are studied in three case scenarios. In addition, a fault insertion tool is utilized in ETAP to check the sequence of relay operation in the modeled microgrid. A three-phase fault is inserted at buses connected to RES or DG in the microgrid and the performance of the protection system and the coordination among the relays are evaluated.

Selective Coordination at Bus 4. TCC Coordination for the Relays Protecting Bus 4 is Shown in Fig. 8. The Sequence of Operation for a Three-Phase Fault Inserted in Bus 4 is Shown in Fig. 9. Symbol ‘×’ Indicates the Relays’ Sequence of Operation.

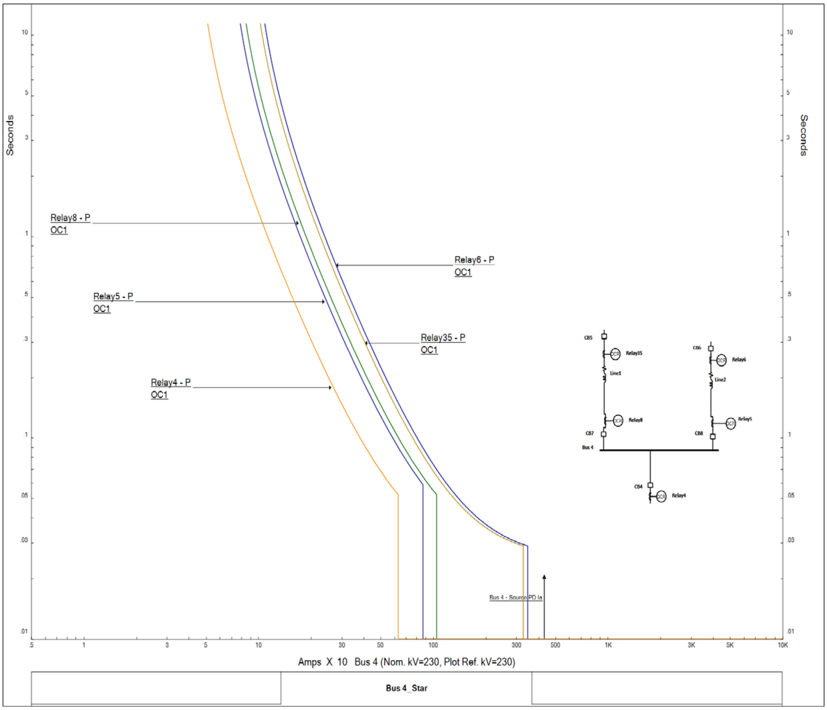

Fig. 8. Relay coordination for maximum fault at bus 4

The simulation results show that the fault is initially detected by relay 4, 8, 5 and tripped by circuit breaker 4, 7, 8 respectively which are the primary protections of the faulted bus. Then, relay 9 is going to take action as backup protection to trip circuit breaker 10, if the primary protection does not act in a proper time. It shows that relay 4 detects a 4.544 kA three-phase fault at 10 ms and trips CB 4 after a time equal to the mechanical delay of the CB which is 33.3 ms (2 cycle). Relay 9 sees the fault after 30.4 ms and opens CB 10 after the mechanical delay.

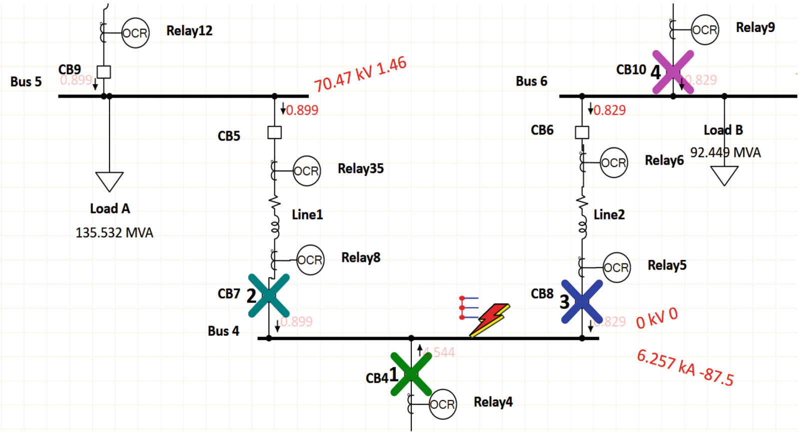

Fig. 9. A three-phase fault insertion in bus 4

Selective Coordination at Bus 7. TCC Coordination for the Relays Protecting Bus 7 is Shown in Fig. 10. The Sequence of Operation for a Three-Phase Fault Inserted in Bus 7 is Shown in Fig. 11. Symbol '×' Indicates the Relays' Sequence of Operation.

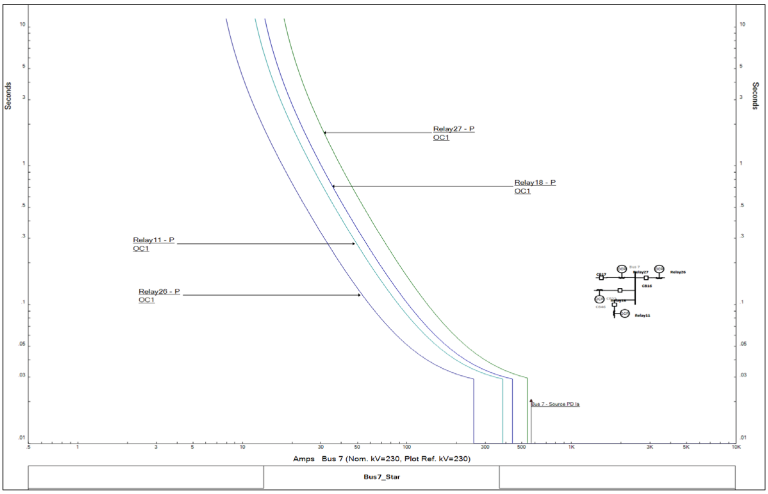

Fig. 10. Relay coordination for maximum fault at bus 7

The simulation results show that the fault is initially detected by relay 11, 18, 27 and tripped by circuit breaker 46, 33, 17 respectively which are the primary protections of the faulted bus. Then, relay 24 is going to take action as backup protection to trip circuit breaker 13, if the primary protection does not act in a proper time. It shows that relay 27 detects a 4.182 kA three-phase fault at 10 ms and trips CB 17 after a time equal to

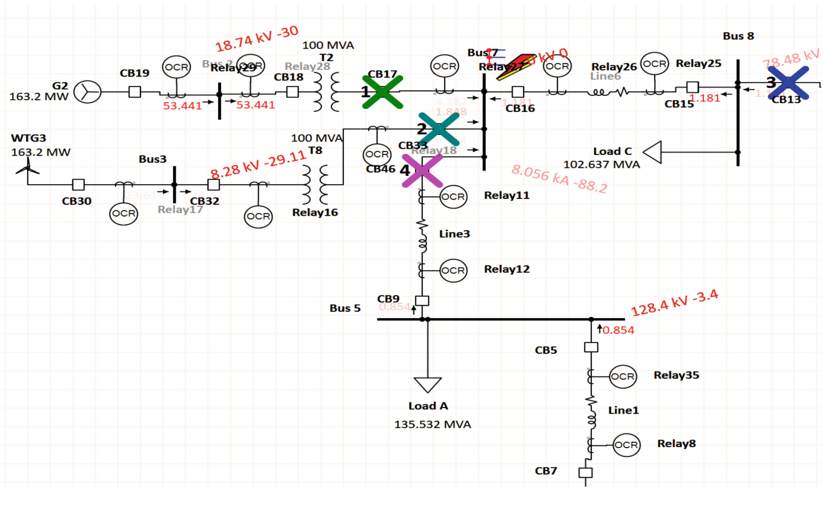

Fig. 11. A three-phase fault insertion in bus 7

the mechanical delay of the CB which is 33.3 ms (2 cycle). Relay 24 sees the fault after 30 ms and opens CB 13 after the mechanical delay.

Selective Coordination at Bus 9. TCC Coordination for the Relays Protecting Bus 9 is Shown in Fig. 12. The Sequence of Operation for a Three-Phase Fault Inserted in Bus 9 is Shown in Fig. 13. Symbol '×' Indicates the Relays' Sequence of Operation.

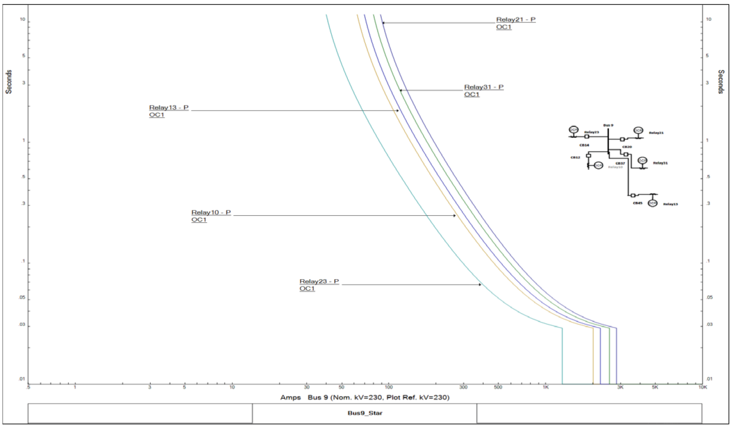

Fig. 12. Relay coordination for maximum fault at bus 9

The simulation results show that the fault is initially detected by relay 21, 23, 10 and tripped by circuit breaker 20, 14, 12 respectively which are the primary protections of the faulted bus. Then, relay 24 is going to take action as backup protection to trip circuit breaker 13, if the primary protection does not act in a proper time. It shows that relay

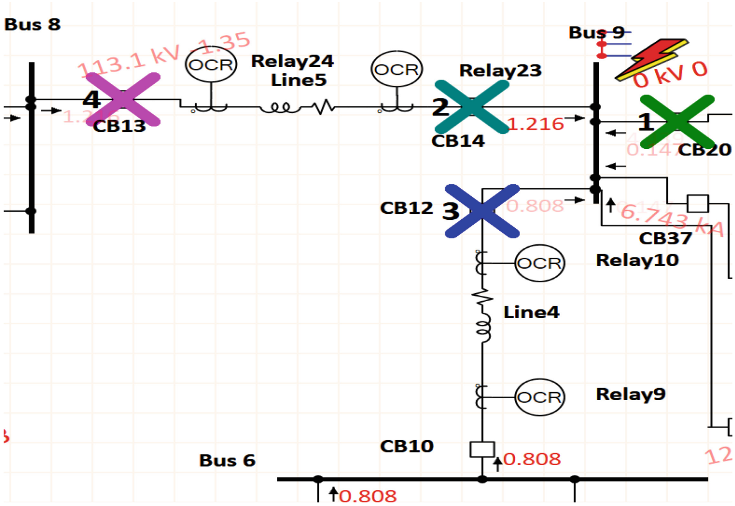

Fig. 13. A three-phase fault insertion in bus 9

21 detects a 4.439 kA three-phase fault at 10 ms and trips CB 20 after a time equal to the mechanical delay of the CB which is 33.3 ms (2 cycle). Relay 24 sees the fault after 30 ms and opens CB 13 after the mechanical delay.

The simulation results show a good coordination with proper CTI between primary and backup protective devices for the faults at buses connected to RES or DG (bus 4, 7, and 9).

6 Conclusions

An IEEE 9 Bus system is modified to simulate a microgrid in ETAP to study the effect of Renewable Energy Sources and Distributed Generation integration on the operation of the microgrid power system. ETAP tools are utilized to run load flow and short circuit analysis in the modeled microgrid with and without PV system integration to ensure the stability of the modeled microgrid under normal operation and contingencies.

Relays and protective devices are added and set in the modeled microgrid to protect all components against over current situations. Therefore, a selective coordination study is required to ensure suitable coordination among the protective devices. An algorithm is proposed that utilizes the results of the load flow and short circuit analysis to optimize the coordination among the protective devices and increase the reliability and selectivity of the system. The simulation results confirm the effectiveness of the proposed approach through optimizing the coordination time interval between the overcurrent relays.

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SSIVD-Net: A Novel Salient Super Image Classification and Detection Technique for Weaponized Violence

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Abstract. Detection of violence and weaponized violence in closed-circuit television (CCTV) footage requires a comprehensive approach. In this work, we introduce the *Smart-City CCTV Violence Detection (SCVD)* dataset, specifically designed to facilitate the learning of weapon distribution in surveillance videos. To tackle the complexities of analyzing 3D surveillance video for violence recognition tasks, we propose a novel technique called *SSIVD-Net* (**S**alient-**S**uper-**I**mage for **V**iolence **D**etection). Our method reduces 3D video data complexity, dimensionality, and information loss while improving inference, performance, and explainability through salient-super-Image representations. Considering the scalability and sustainability requirements of futuristic smart cities, the authors introduce the *Salient-Classifier*, a novel architecture combining a kernelized approach with a residual learning strategy. We evaluate variations of SSIVD-Net and Salient Classifier on our SCVD dataset and benchmark against state-of-the-art (SOTA) models commonly employed in violence detection. Our approach exhibits significant improvements in detecting both weaponized and non-weaponized violence instances. By advancing the SOTA in violence detection, our work offers a practical and scalable solution suitable for real-world applications. The proposed methodology not only addresses the challenges of violence detection in CCTV footage but also contributes to the understanding of weapon distribution in smart surveillance. Ultimately, our research findings should enable smarter and more secure cities, as well as enhance public safety measures.

Keywords: Violence detection · Weaponized violence detection · Action recognition · Signal processing · Smart surveillance

1 Introduction

Violence and gang-related activities can pose a serious threat to a city, particularly when authorities are unable to respond quickly enough to prevent further

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damage. In some cases, these incidents can result in loss of life and property, especially when weapons are involved. Regrettably, incidents of road rage, gang-related violence, and other spontaneous acts of violent crime frequently occur without prior warning or the ability for authorities to intervene proactively. These events pose a considerable challenge for law enforcement agencies and other relevant authorities. Unfortunately, the reporting of such incidents often occurs after the fact, leaving authorities with limited options for timely intervention and effective prevention.

Although surveillance systems have helped authorities identify instigators and culprits through recordings, it often takes too long to detect, search, and arrest someone after a crime is committed. To reduce turnaround time and increase efficiency, there is a growing need for automated detection and signaling systems. Since the breakthrough of deep learning [12] in the ImageNet 2012 competition, deep neural networks (DNNs) have become the go-to AI technology for automating such tasks. By leveraging DNNs and other AI techniques, smart cities worldwide can better detect and respond to violence, safeguarding lives and properties. The benefits of such technologies are clear; for instance, integrated surveillance systems equipped with advanced AI algorithms can analyze real-time video feeds from CCTV cameras to identify and alert authorities to potential violent incidents, enabling swift intervention. Furthermore, AI-powered predictive analytics can analyze various data sources, including social media feeds and sensor data, to identify patterns and trends associated with violence, enabling authorities to allocate resources strategically and prevent outbreaks of violence in specific areas. As these technologies evolve, they will play an increasingly important role in maintaining safety and security in our cities.

Current violence detection methods predominantly rely on spatiotemporal models to identify instances of violent activities within video footage. However, it is essential to recognize that violence encompasses a wide range of behaviors, spanning from physical altercations to gunfights. Treating all violent events equally may not effectively prioritize the severity or potential harm involved. To address this challenge, it becomes crucial to develop methods to detect weapons in surveillance footage.

Existing research has primarily concentrated on identifying weapons using object detection models. Still, these approaches rely on datasets limited to specific weapon types, such as knives and guns. While this provides valuable insights into the detection of known weapons, it fails to account for the reality that virtually any object can be utilized as a weapon in an act of violence. Therefore, there is a pressing need for further research and advancements in open-world weapons detection, which can efficiently identify and classify a broader range of objects that may be employed as weapons. Expanding weapons detection beyond predefined categories equips surveillance systems to recognize potential threats and intervene effectively, improving public safety. Exploring novel approaches and advancements in deep learning, computer vision, and object recognition enables comprehensive open-world weapons detection. These advancements aid in crime prevention and enhance overall community security and well-being.

Furthermore, 3D and spatio-temporal models such as C3D [26], I3D [3] and ConvLSTM [25], as well as object detection models like You-Only-Look-Once (YOLO) [18] and RCNN [7], require a high computational load to achieve state-of-the-art performance in violence and weapons detection. This leads to increased carbon footprints in smart cities. We aim to address these challenges by developing a more efficient image classifier capable of accurately detecting weaponizing violence while promoting sustainability in smart cities. To achieve this, we contributed the following:

- We address the challenges of detecting violence and weapons in CCTV footage by introducing the *Smart-City CCTV Violence Detection (SCVD)* dataset. Our dataset is designed to facilitate the learning of weapon distribution in surveillance videos, enabling DNNs to effectively detect both weaponized and non-weaponized violence.
- We propose *SSIVD-Net* (**S**alient-Super-**I**mage for **Vi**olence **Det**ection) as a data-centric approach to address the challenges associated with 3D surveillance video in violence recognition tasks. Our approach involves transforming the 3D video data into a Salient-Super-Image representation, reducing data complexity and dimensionality. This transformation enables faster inference, improved performance, and simplified explainability. In particular, our approach allows for seamless integration with 2D vision classifiers, which are not commonly used in the field.
- The authors introduce a novel architecture called *Salient-Classifier*, that leverages a kernelized approach with residual networks [9]. We evaluate variations of SSIVD-Net and Salient-Classifier on our dataset and benchmark against SOTA models used in violence detection. Additionally, we perform comparative analyses to demonstrate the effectiveness of our model using other violence datasets.

Through our contributions, we aim to advance the SOTA in violence and weaponized violence detection while also providing a practical and scalable solution for real-world applications.

The rest of the paper is structured as follows: Sect. 2 discusses the relevant literature on violence detection, Sect. 3 introduces the SCVD dataset, Sect. 4 describes the proposed methodology and its components, Sect. 5 presents the experimental results and comparative analysis, and Sect. 6 concludes the paper with potential future directions.

2 Related Work

2.1 Weapon Detection

There are two main approaches to Object Detection: YOLO [18], and RCNN [7]. YOLO involves taking sliding windows of fixed sizes from the input image at every possible location and feeding them into an image classifier for inference. At the same time, RCNN proposes regions to feed into the classifier. Since their inception, research has gone into optimizing these methods to achieve better performance [8,20], faster inference [19,21], or both [2,6,29].

To detect weapons in surveillance footage, researchers have leveraged the Faster RCNN object detection model for its high accuracy in identifying objects of interest [11,27]. However, transfer learning has also been applied to pre-trained Faster RCNN models for detecting handheld guns in clustered scenes [27]. To classify mostly guns and knives, an ensemble method combining Faster RCNN and Single Shot Detector has been explored [11]. Another study used a pre-trained YOLO-V4 model on similar datasets [1]. However, these methods are limited in their ability to generalize to a wider range of objects that could be used as weapons, and they have not been trained on datasets that include CCTV footage, which limits their ability to detect weapons in various types of video.

2.2 Violence Detection

While there are multiple attempts to detect weapons from videos only, there are works that aim to detect violence from videos and CCTV footage. For example, [13] used InceptionNet to detect violence in every frame from sports videos and movies. This results in slower inference and poor generalization results as their method failed to learn temporal properties connecting frames within similar video embeddings. For their models to not lose temporal information, [24] and [23] used ConvLSTMs to detect violence in CCTVs. In ConvLSTMs, an image classifier is employed for spatial feature extraction, while LSTMs learn the temporal information. The authors in [23] used a pre-trained ResNet50 model to extract spatial features from the video frames while [24] leveraged the VGG16 architecture. The extracted features are then concatenated with the latent features from the LSTM [22]. The above techniques and models require a lot of computing resources to get the results.

Our approach differs from previous techniques as we aim to create a novel data-centric approach that enables image classifiers to learn spatial and temporal features for efficient weaponized violence detection in CCTV videos. We build upon the super image approach, first proposed in [5], and showcase Salient-Super-Image to minimize the information lost due to rearranging and resizing video frames into 2D images. Our study is the first to investigate open-world weaponized violence detection in surveillance systems.

2.3 Super-Image

The field of action recognition for video classification has been gaining attention in recent years as it plays a significant role in video understanding. Most approaches in this domain use 3D convolutions to classify videos based on appearance, depth, or body skeletons. However, [5] proposed a different approach using a 2D image classifier (SIFAR). They argued that instead of using deep 3D networks for video action recognition tasks, a simple image classifier could work. To accomplish this, they introduced a technique that involves extracting frames from videos, resizing them, and combining them into a composite image. This