Real-Time Machine Learning for Power Grid SCADA Alarm Event Detection Decision Support

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Summary

- Introduction
- Methodology
  - Alarm event detection model training
  - Alarm event decision support
- Empirical Study
- Conclusion

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Introduction

- Intelligent analysis and regulation
  - Enhancing power grid efficiency and reliability.

- Supervisory Control And Data Acquisition (SCADA) and Energy Management System (EMS)
  - Two major systems for power fault detection.

- Detect anomalous behaviors in SCADA systems is the key challenge.

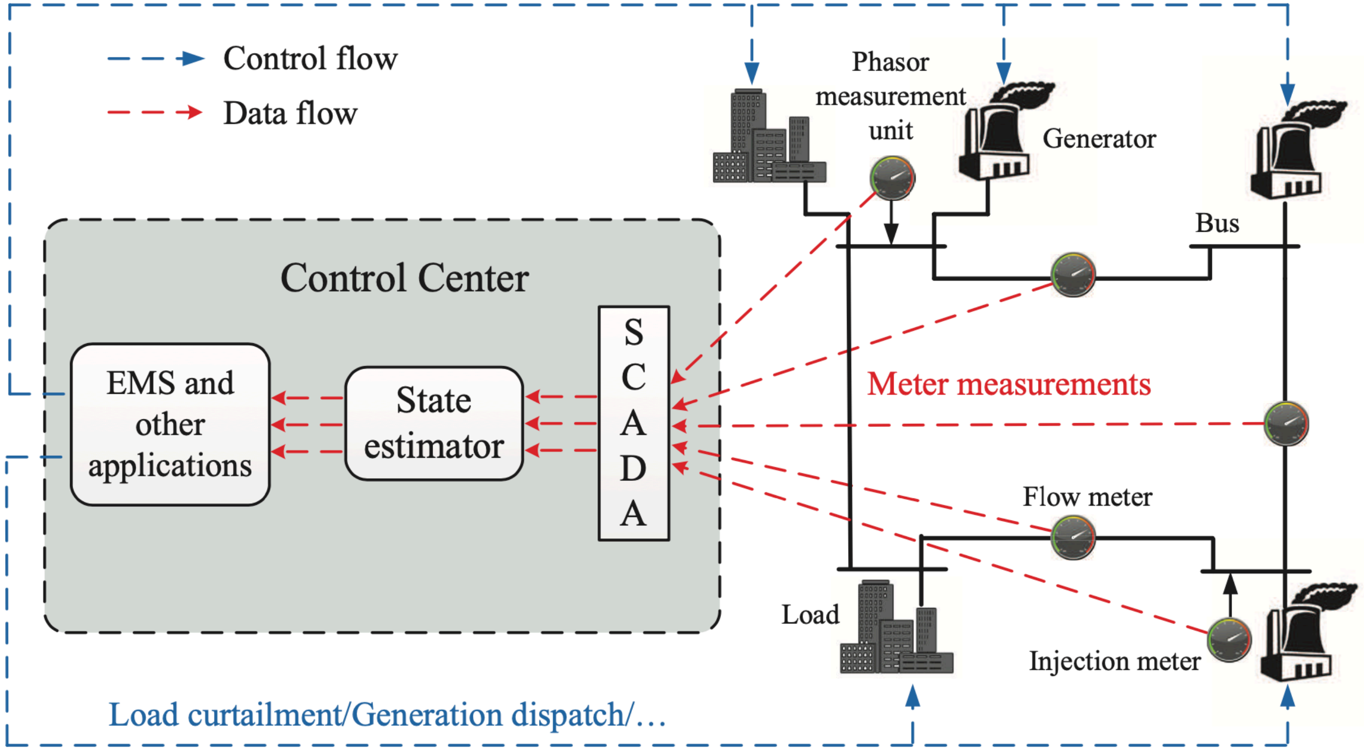

Fig. 1 The operation of the SCADA/EMS system in power grid [1]

Introduction

- Intelligent alarm processing in power systems
  - Rule-based systems for alarm classification. [2,3]
  - Expert systems: make decision support faster. [4,5,6]
  - Mixed integer linear programming for false alarms detection. [7,8]
- **Motivation:**
  - Current research on real-time power system SCADA setups remains limited.
  - A critical need exists to develop solutions for the early detection and mitigation of potential stability events.
  - Previous work focuses primarily on peak alarm periods, leaving operators with insufficient time to respond to incidents and learn from past experiences.

Introduction

- **Contributions:**
  - Novel Deep Neural Network (DNN) Framework
    - **Offline training** using historical alarm data for robust generalization.
    - **Accurate detection** of critical SCADA alarm events, especially during peak periods when operators require enhanced decision-making support.
  - Online Decision Support Framework
    - Combines a **pre-trained DNN** with a **large language model (LLM)**.
    - **Real-time alarm detection** and prioritization of event information based on historical urgency and relevance.
    - Provides a **holistic view** for operators, supporting **quick and informed decision-making.**

Methodology

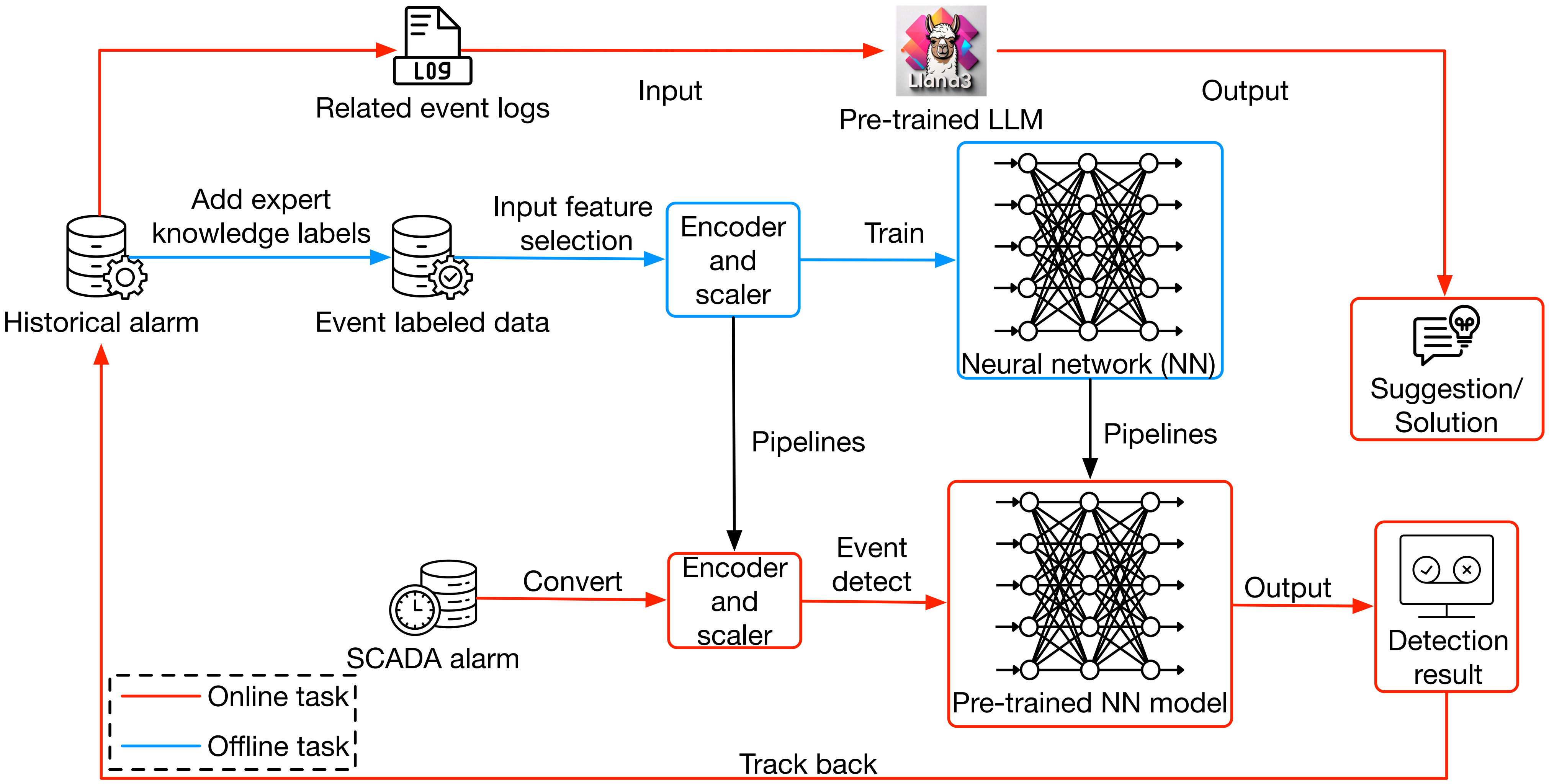

Fig. 2 The framework of developed alarm event detection system.

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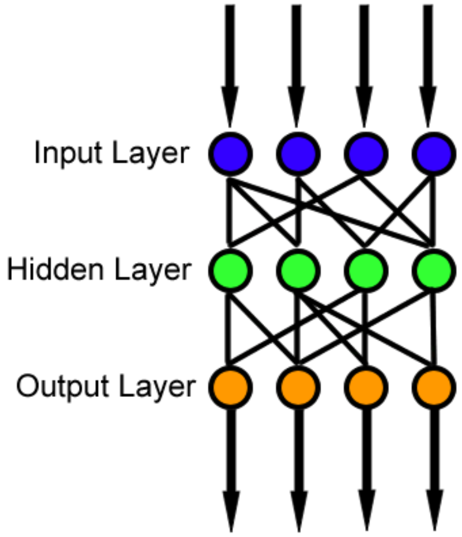
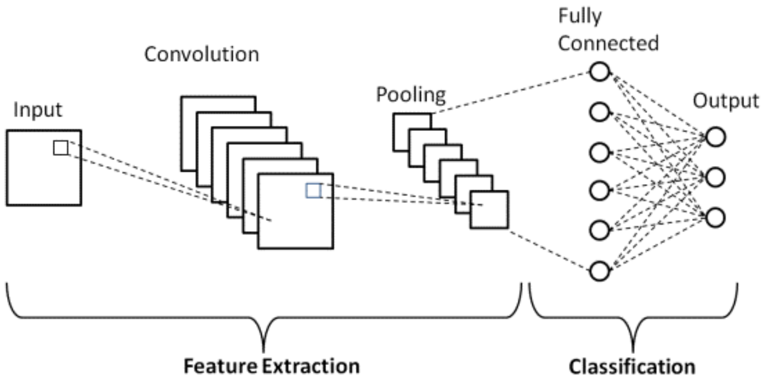
Neural Network Comparison for SCADA Alarm Detection

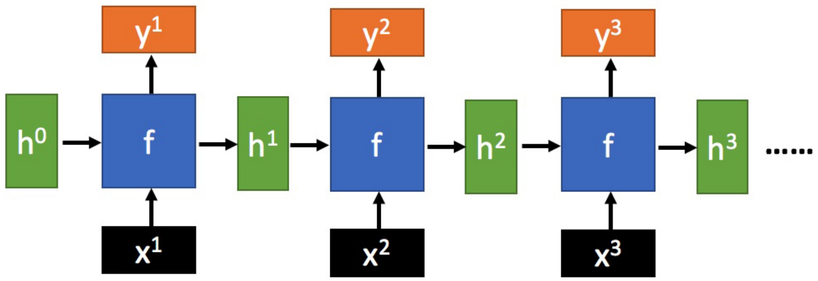
Architecture	Operation	Strengths	Limitations	Suitability for SCADA
FNN	Sequential processing, no data assumptions	Versatile, simple, scalable	Requires large data & time for training	**Best fit**
CNN	Pattern recognition in hierarchical layers	Great for feature extraction (images)	Not suitable for non-hierarchical data	**Not ideal**
RNN	Processes sequential data, maintains memory	Good for time-series & evolving data	Struggles with chaotic, unordered inputs	**Not suitable**



Feedforward Neural Network FNN



Convolutional Neural Network (CNN)



Recurrent Neural Network (RNN)

Alarm event decision support

- This distance measure serves as a generalized form encompassing both **Euclidean** and **Manhattan** distance metrics [9]

$$SD = \left(\sum_{i=1}^{n} |e_i - E_i| \right)^{1/p}$$

where e_i represents the detected alarm event, while E_i denotes a previous alarm event. The parameter p signifies the order of the norm.

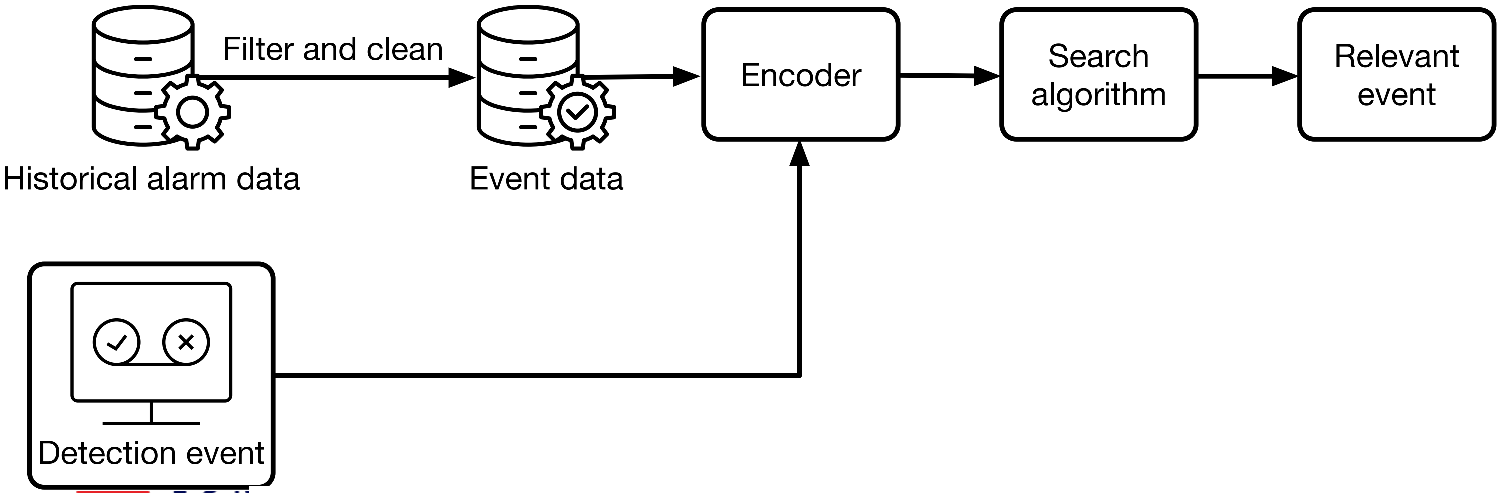


Fig. 3 The relevant alarm event searching process.

Algorithm 1. Historical Event Search and Decision Support

procedure
  Encoding input features of historical and detected events $\{\mathbf{E}, e\}$
  for Each historical event $E \in \mathbf{E}$ **do**
    Calculate SD between E and e by Eq.(5);
  end for
  Obtain minimal distance historical event E';
  Find the log of E'
  Input e, E', the log of E' to LLM
  Input related questions
  Return answers from LLM
end procedure

Empirical Study

- **Chattering event detection**
  - SCADA alarm data:
    - From May 1, 2017, to May 25, 2017.
    - Training set: from 00:00:00 on May 1, 2017, to 23:59:59 on May 24, 2017.
      - 2,572,919 chattering events and 2,132,938 non-chattering events.
    - Testing set: from 00:00:00 to 01:00:00 on May 25, 2017.
      - 3,717 chattering events and 3,035 non-chattering events.

	EventId	EventTimeStamp	SCADA_Category	TOC	AOR	Priority_Code	Substation	DeviceType	Device	event_message	chattering
0	26	2017-05-01 00:00:04	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1089	#1 PRIMARY RELAY FAIL	1
1	45	2017-05-01 00:00:06	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1089	#1 PRIMARY RELAY NORMAL	1
2	147	2017-05-01 00:00:47	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1089	#1 PRIMARY RELAY FAIL	1
3	150	2017-05-01 00:00:49	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1089	#1 PRIMARY RELAY NORMAL	1
4	108	2017-05-01 00:00:31	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1090	#2 PRIMARY RELAY FAIL	0
5	125	2017-05-01 00:00:35	MH	TMS	TOCGR	3	Substation1002	RELAY	Device1090	#2 PRIMARY RELAY NORMAL	0
6	39	2017-05-01 00:00:05	MH	TMS	TOCGR	3	Substation1049	BLKCAR	Device643	SIGNAL RECEIVED NORMAL	0
7	18	2017-05-01 00:00:03	ML	TMS	TOCSR	4	Substation1051	BLKCAR	Device292	SIGNAL RECEIVED TRIP ENABLED	0

Empirical Study

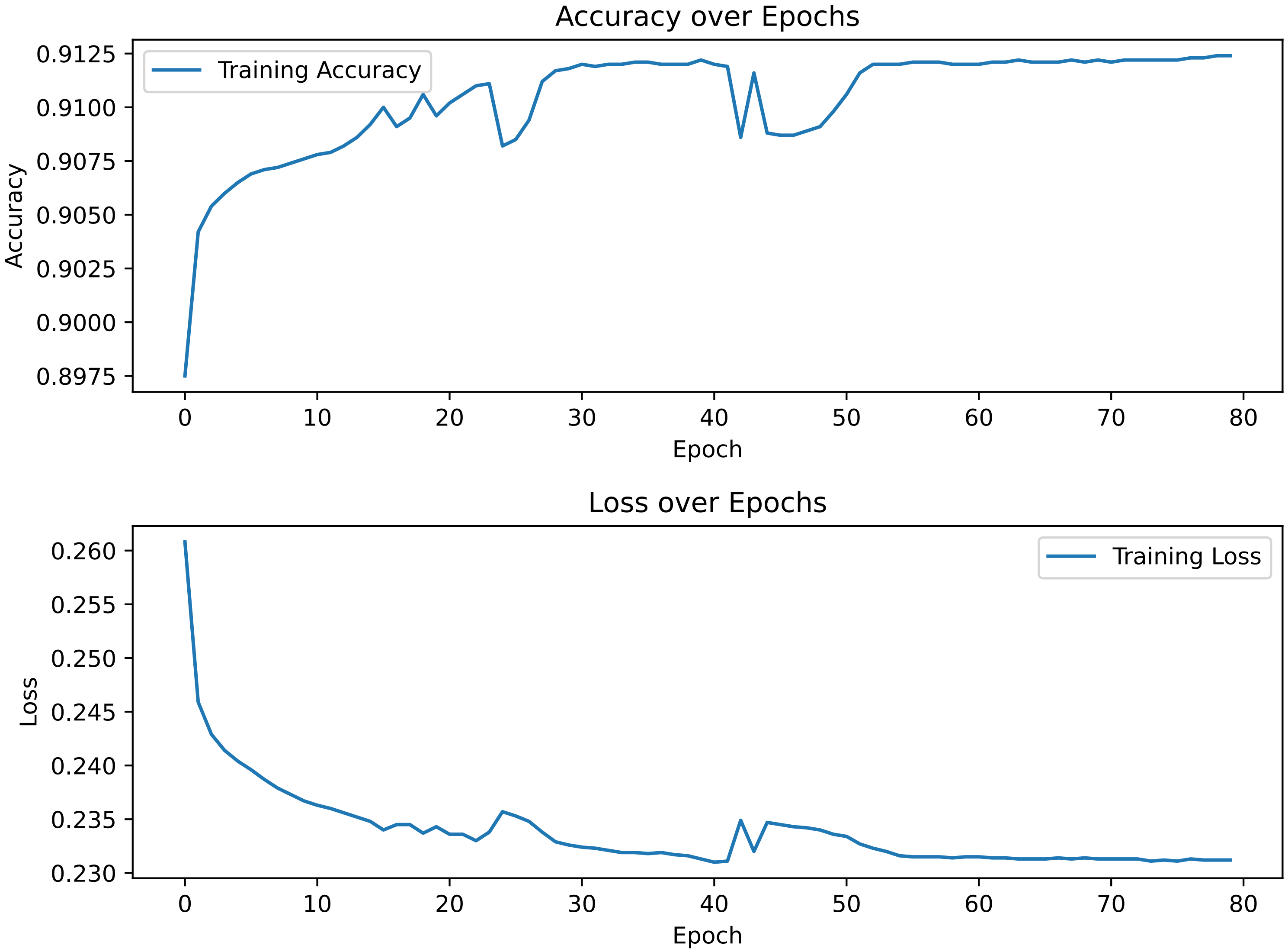


Fig. 4 The training accuracy and loss of proposed DNN

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Empirical Study

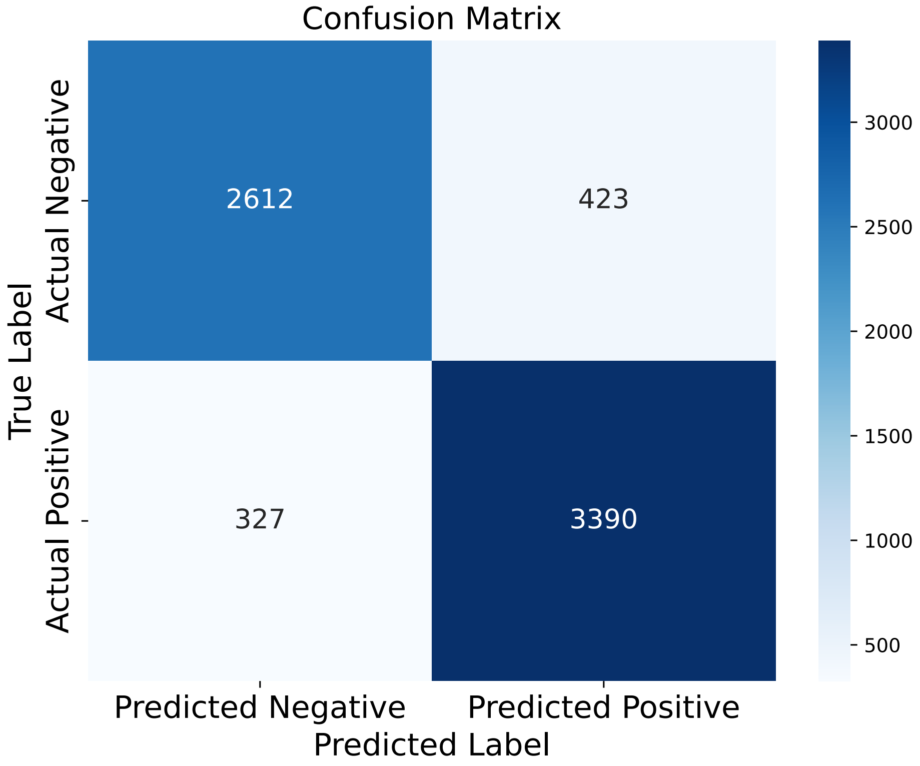


Fig. 5 The confusion matrix of testing data.

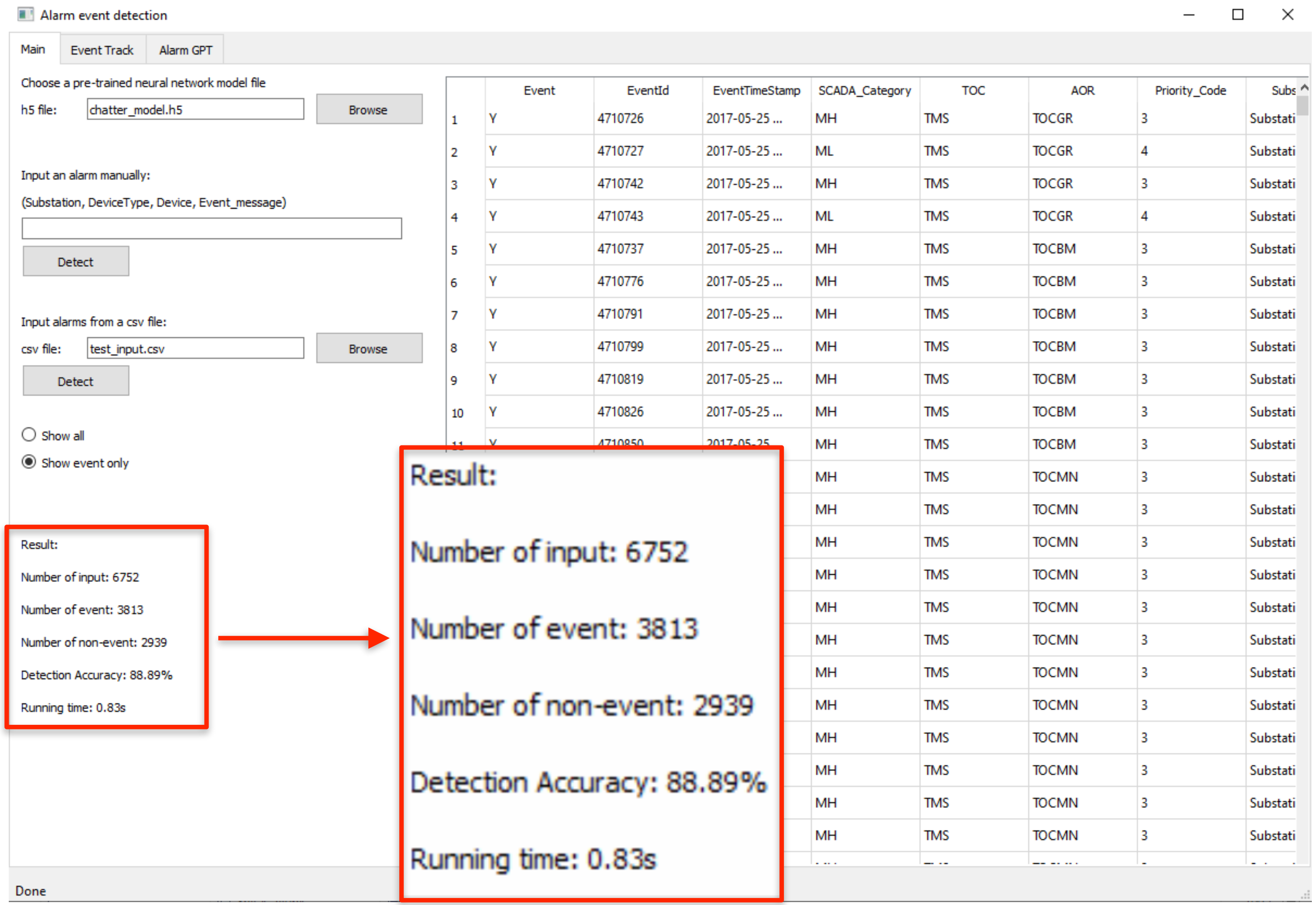
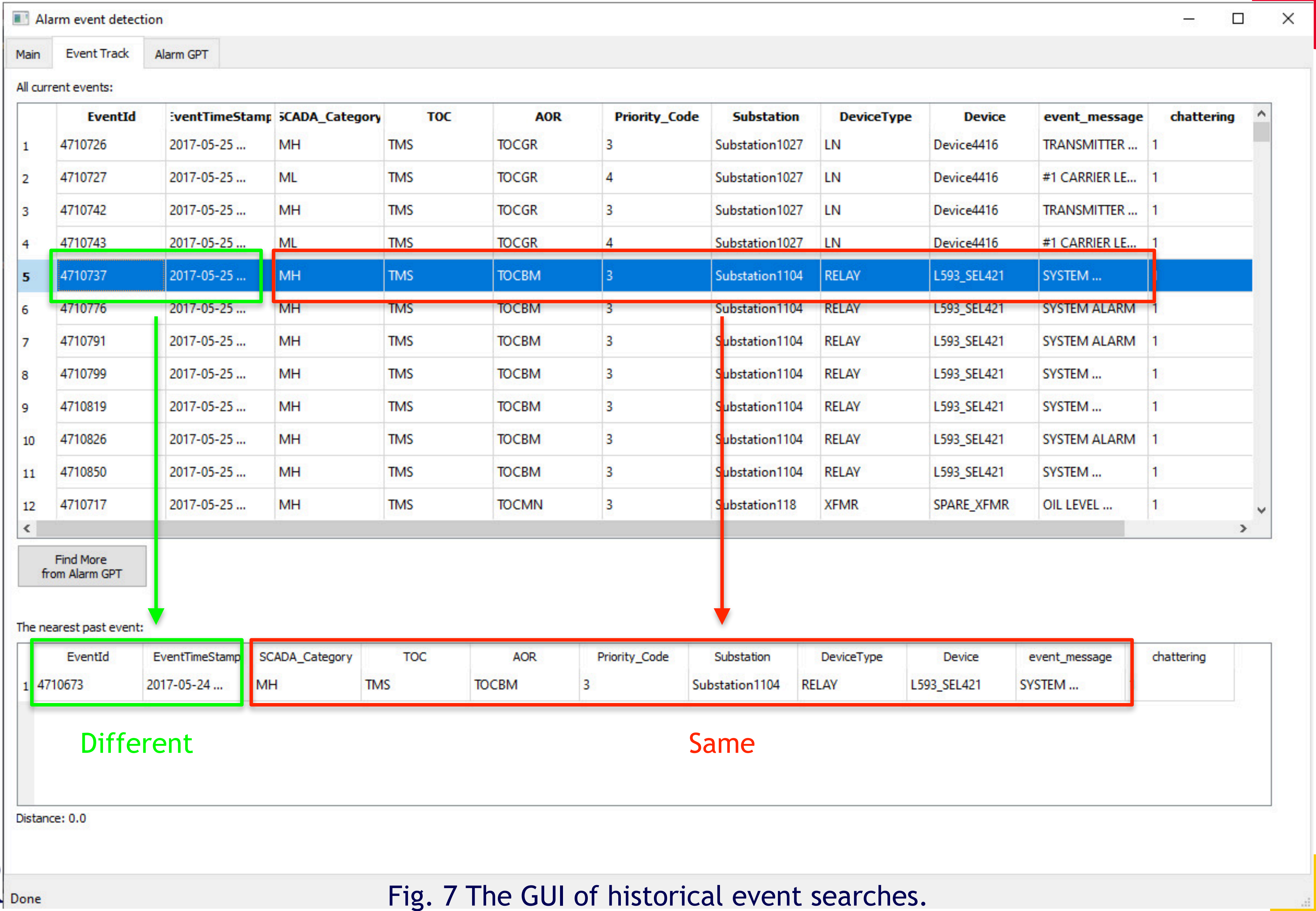


Fig. 6 The real-time SCADA alarm event detection.



	EventId	EventTimeStamp	SCADA_Category	TOC	AOR	Priority_Code	Substation	DeviceType	Device	event_message	chattering
1	4710726	2017-05-25 ...	MH	TMS	TOCGR	3	Substation1027	LN	Device4416	TRANSMITTER ...	1
2	4710727	2017-05-25 ...	ML	TMS	TOCGR	4	Substation1027	LN	Device4416	#1 CARRIER LE...	1
3	4710742	2017-05-25 ...	MH	TMS	TOCGR	3	Substation1027	LN	Device4416	TRANSMITTER ...	1
4	4710743	2017-05-25 ...	ML	TMS	TOCGR	4	Substation1027	LN	Device4416	#1 CARRIER LE...	1
5	4710737	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ...	
6	4710776	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ALARM	1
7	4710791	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ALARM	1
8	4710799	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ...	1
9	4710819	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ...	1
10	4710826	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ALARM	1
11	4710850	2017-05-25 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ...	1
12	4710717	2017-05-25 ...	MH	TMS	TOCMN	3	Substation118	XFMR	SPARE_XFMR	OIL LEVEL ...	1

	EventId	EventTimeStamp	SCADA_Category	TOC	AOR	Priority_Code	Substation	DeviceType	Device	event_message	chattering
1	4710673	2017-05-24 ...	MH	TMS	TOCBM	3	Substation1104	RELAY	L593_SEL421	SYSTEM ...	

Fig. 7 The GUI of historical event searches.

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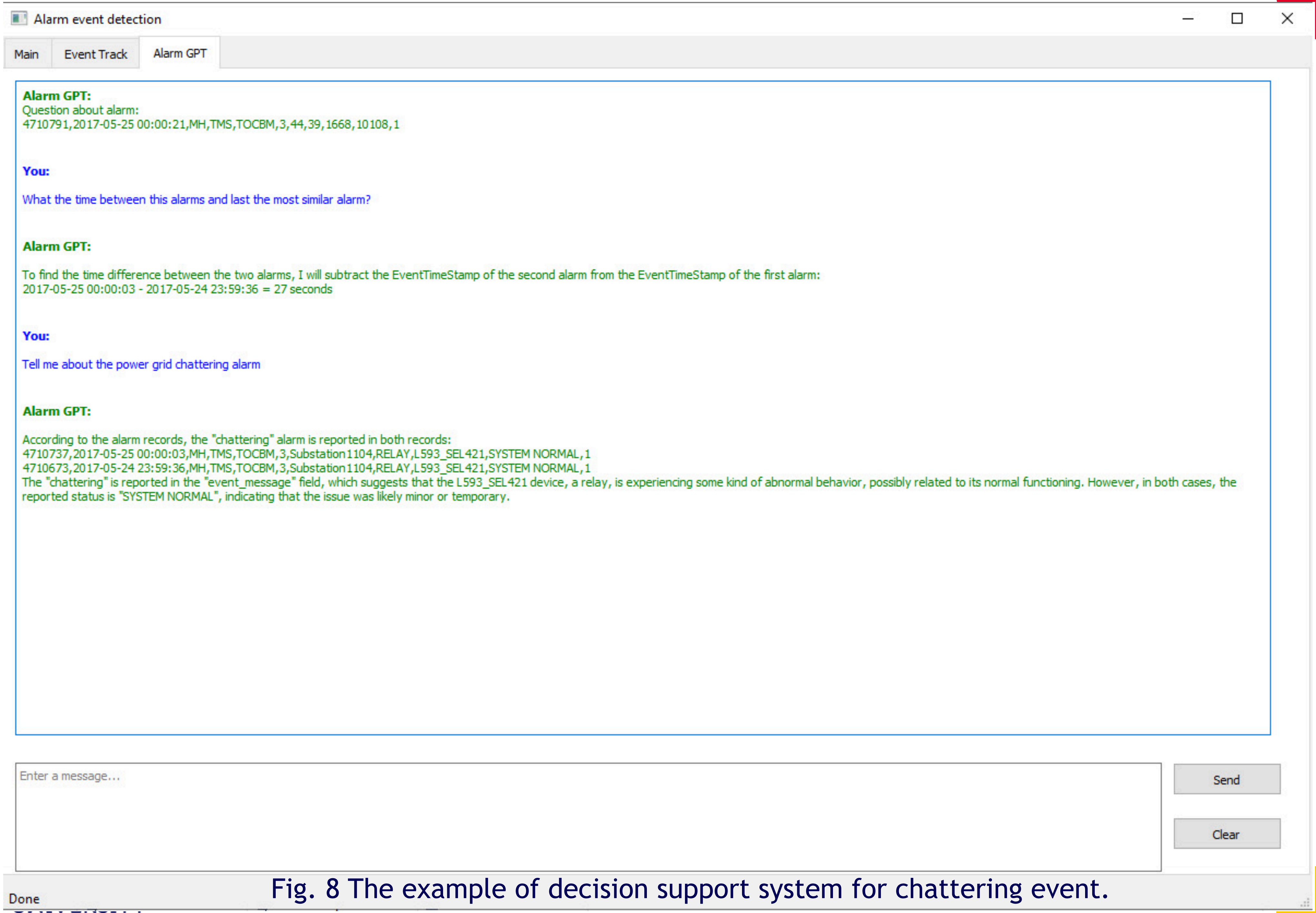

Fig. 8 The example of decision support system for chattering event.

Conclusion

- A real-time machine learning framework was developed specifically for SCADA alarm event detection.

- The introduction of a DNN architecture enhances the ability to efficiently detect real-time alarm events.

- A specialized algorithm for historically relevant event search supports decision-making.

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Thanks for Listening

Questions?

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