International Journal of Research
Available at https://journals.pen2print.org/index.php/ijr/
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 06 Issue 03
March 2019

Fog Computing Aided Process Monitoring System Using Benchmark System for Large-Scale Data-Driven Smart Manufacturing

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ABSTRACT-- *Animated by the ongoing advancement of fog computing innovation, in this paper, a fog computing aided process monitoring and control architecture is proposed for large-scale industrial processes, which empowers reliable and effective online performance optimization in each fog computing hub without changing pre-designed control subsystems. Also, a closedloop data-driven method is produced for the process monitoring system design and an adaptive arrangement approach is proposed to manage the issues brought about by the progressions of process parameters and working focuses. The possibility and viability of the proposed design approaches are checked and showed through the contextual analysis on the Tennessee Eastman (TE) benchmark system.*

Index Terms-- Fog computing, data-driven methods, process monitoring, adaptive methods, large-scale process, distributed control..

I. INTRODUCTION

THis , driven by the quick improvement of information and correspondence advancements just as computer science, the incredible changes of the industrial environment has been seen these days [1], [2]. Particularly, invigorated by the wide use of the Internet of Things (IoT), the sharing and cross-preparation of the data for a superior coordination and worldwide choice have picked up bunches of consideration in these years. Among the created communication/calculation advances, fog is a doable and reliable architecture which disperses calculation, correspondence, control nearer to the end clients along the cloud-to-things continuum [3]. A burst of the effective uses of fog computing procedure can be seen as of late, see e:g: [2], [4]– [6]. In any case, bunches of difficulties still stay amid the genuine utilization of fog computing method [3], [7].In present day industry, with the expanding requests on item quality and monetary advantages, the advanced industrialhigh self-ruling degrees and moder as twellbeing and dependability, amid the last a couple of decades, show based blame analysis and blame tolerant control advances have been broadly examined and confirmed both from scholastic and industrial fields, in which a process display is fundamental for the design of the monitoring and control systems, see e:g: [8]– [10] and the references in that. Helped by the improvement of correspondence technology, data organizing systems just as computer science, in the previous 30 years, the data-driven methods have attracted extensive consideration both hypothetical and down to earth spaces. The real focal points brought by the data-driven systems are that the tedious and high-engineer-endeavors required demonstrating strategy could be saved money on the one hand, then again, the hard to-be-gained process data on the abnormalities or deficiencies can be effectively disconnected from accessible process data. In writing, various scholastic looks into and industrial uses of data-driven blame finding procedures can be discovered, see e:g: [11]– [18] and the references in that.

Be that as it may, the greater part of the current data-driven designs result in a focal computing technique where the worldwide data is required. For a large-scale industrial process, the entire design in manner includes tremendous computational and communicational load, particularly when an online arrangement of the designed monitoring and control systems is requested. So as to discharge the focal computational weight and diminish the correspondence endeavors among detached subsystems, the decentralized monitoring and control advances, see e:g: [19]– [25] and the references in that, could be used. In this paper, persuaded by the points of interest brought by fog computing procedure, a fog computing aided process monitoring and control architecture is right off the bat proposed for large-scale industrial processes. Contrasting from the current decentralized screen ing and control methodologies, the proposed one maintains a strategic distance from the modification of pre-designed control systems and empowers online performance optimization in each fog computing hub with solidness ensure. Also, a data-driven design method is

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 06 Issue 03
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created for the process monitoring system in which the impacts of the nearby input system on the process data are considered. Also, an adaptive setup approach is proposed for the designed data-driven process monitoring system in each fog computing hub to manage the issues brought about by the progressions of process parameters and working focuse.

II.RELATED WORK

A. Fog computing architecture

The fog architecture for IoT applications can be characterized on a 3-level premise, as portrayed in Fig 1. The main level (Tier 1) relates to the end purposes of the system, containing the crude data produced by the sensors which go about as data sources. This level subsequently can be portrayed as the one containing the terminal hubs comprising of IoT gadgets. The following level (Tier 2) is the fog computing layer, additionally alluded to as the fog/edge knowledge. This contains gadgets, for example, switches, passages, switches, and so on – the ones that are fit enough to process, figure and incidentally store the got data. These fog gadgets are associated with the cloud system, and send data to the cloud occasionally. The third and last level (Tier 3) is the distributed computing layer, which compares to cloud insight and is equipped for putting away and processing huge measure of data, contigent upon the capacity data focuses.

A conventional fog architecture can be thought as a three level system structure4, as appeared in Fig. 1

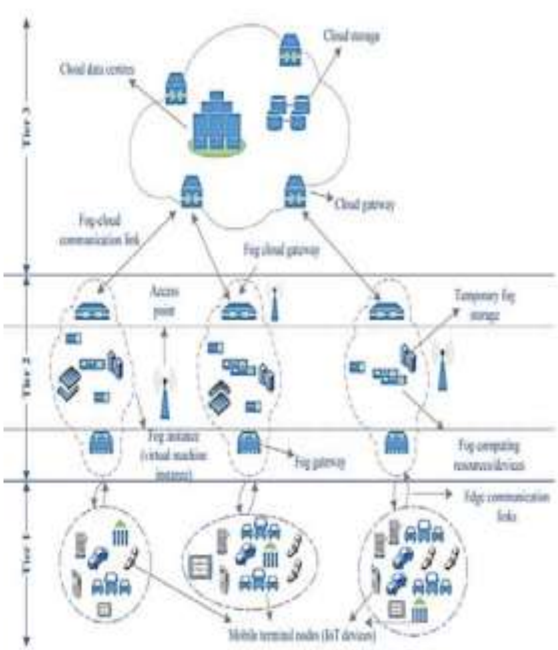

Fig. 1. Fog computing architecture

B. Process monitoring

Savvy sensors are a vital component in assembling expert cess monitoring. To gather ongoing data from industrial facility floors and screen the wellbeing states of assembling hardware and processes, sensors or sensor arranges that can distinguish occasions and measure signals are required. Wright et al. [29] built up a condition-based monitoring system for foreseeing cutting instrument wear and surface complete the process of utilizing accelerometer-based remote sensor systems. The remote sensor stage dependent on the IEEE 802.15.4 standard was utilized to gauge the vibrations of a fast steel end processing instrument. The remote detecting system was exhibited to most likely measure cutting conditions, for example, apparatus wear of the processing machine. Rangwala and Dornfeld [30] proposed a compu-tational structure for keen apparatus condition monitoring utilizing neural systems and different sensors. An acoustic outflow trans-ducer was mounted on the instrument shank to gauge vibrations. A power dynamometer was utilized to gauge cutting powers. Exper-imental results have demonstrated that the monitoring system dependent on the structure had the capacity to perform sensor combination and recognize process irregularities. Li and Li [31] built up a direction condi-tion monitoring system for recognizing the beginning of weariness breaks utilizing acoustic emanation sensors. To watch fast arrival of neighborhood ized stress vitality, AE transducers were mounted on the bearing lodging. Lu et al. [32] built up an on the web and remote vitality mon-itoring and blame indicative system for industrial engine systems utilizing remote sensor systems. An in-line torque transducer was utilized to gauge the pole toque of the engine. An optical encoder was utilized to quantify the speed of the engine. The monitoring sys-tem was exhibited in a genuine industrial condition. Hou and Bergmann [33] exhibited an industrial remote sensor organize for machine condition monitoring and blame determination. Standard wire-less correspondence conventions (e.g., IEEE 802.15.4, IEEE 802.11, and IEEE 802.15.1), ZigBee, and WirelessHART were coordinated into the machine condition monitoring system. The proposed system was shown by a lot of investigations on a solitary stage acceptance engine.

C. Finding and visualization

The goal of process monitoring is to evaluate the wellbeing states of machine parts (e.g., direction and axles), fabricating processes (e.g., machining and joining), and manu-facturing systems [34– 37]. Finding is centered around blame recognition, separation, and distinguishing proof. Guess is centered around foreseeing the rest of the time before a machine segment or a manu-facturing system will never again play out its expected capacity because of blame spread and movement. The anticipated time is alluded to in the writing as staying helpful life (RUL). In the course of recent decades, numerous data-driven methods for finding and visualization in assembling have been created. In particular, data-driven methods for finding can be characterized into flag processing strategies [38,39], computerized reasoning [40], design acknowledgment examination, and factual learning [41]. The traditional data-driven methods for anticipation incorporate autoregressive (AR) demonstrate, bilinear model, multivariate adaptive relapse, neural systems, fluffy set hypothesis, and AI. Not at all like material science based meth-ods, data-driven finding and anticipation don't require profound comprehension of the material science fundamental machining processes and complete knowledge of the system practices. Instead of model-based methods, data-driven analysis and guess don't require accepted probabilistic dispersions, for example, Gaussian-Markov ace cesses. In correlation with factual methods, AI-based methods, for example, AI don't expect certain stochastic or ran-dom processes, for example, Wiener processes and Gamma processes, in spite of the fact that AI requires large volumes of preparing data sets and elite computing stages, for example, cloud com-puting.

D. Framework, cloud and fog computing

Existing process monitoring systems and prognostic methods have constrained ability of gathering and putting away large volumes of data in distributed settings and restricted computational limit with regards to breaking down these data progressively. Encourage and Carl Kesselman proposed the idea of framework computing in 1999 [42]. A com-putational framework alludes to an equipment and programming foundation that gives reliable, steady, inescapable, and reasonable access to top of the line computational capacities [43]. The idea of distributed computing depends on framework computing. As indicated by NIST, distributed computing is "a model for empowering universal, advantageous, on-request arrange access to a common pool of configurable com-puting assets (e.g., systems, servers, stockpiling, applications, and administrations) that can be quickly provisioned and discharged with smaller than usual mal the executives exertion or specialist organization connection." The expression "Cloud" is regularly utilized as a similitude for the Internet, and alludes to both equipment and programming that convey applications as administrations over the Internet.

To broaden distributed computing and convey elite com-puting ability to the edge of an undertaking's system, fog computing was presented by Cisco [44]. Fog computing, otherwise called edge computing or fogging, is a computing model that gives superior computing assets, data stockpiling, and systems administration benefits between edge gadgets (e.g., remote switch and wide zone arrange get to gadget) and distributed computing data cen-ters [45– 47]. In distributed computing, the enormous measures of data must be transmitted to data focuses on the cloud, yielding critical performance overhead. Rather than distributed computing, compu-tationally concentrated remaining tasks at hand, for example, preparing large datasets and envisioning data investigation are directed in fog computing at loca-tions where large volumes of data are gathered and put away rather than brought together distributed storage. One of the key advantages of fog com-puting is that it empowers clients to abstain from exchanging various data between edge gadgets and distributed computing data focuses by mov-ing computing hubs closer to nearby physical articles or gadgets and executing applications straightforwardly on enormous data. Since fog comput-ing is in closeness to the wellspring of crude data, fog computing can significantly lessen idleness. This is especially impor-tant for inactivity touchy applications. Cisco connected fog computing into keen frameworks in which vitality load adjusting applications are executed on edge gadgets, for example, shrewd meters, empowering constant applications and area touchy administrations [48]. Another key fea-ture of fog computing is that it is a compelling methodology for verifying cloud-based assembling systems [49]. In summary,the related work displayed in this segment expands on past research to investigate how the wellbeing states of machines can be observed utilizing sensors just as how prescient models can be produced for forecast. Be that as it may, existing monitoring sys-tems and prognostics approaches are not fit for gathering the large volumes of continuous data or building large-scale prescient models because of the absence of omnipresent sensor systems, manufactur-ing industry principles, and adaptable elite computing systems. In this paper, remote sensors, distributed computing, and AI are coordinated to address the gap.

III. PROPOSAL METHODOLOGY

A. Data-driven design of the fog computing aided process monitoring system

In this segment, a data-driven plan is proposed to design the fog computing aided process monitoring system. Moreover, so as to adapt to the progressions of the process parameters or working focuses, an adaptive setup approach is created.

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Available at https://journals.pen2print.org/index.php/ijr/
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Data-driven process monitoring system design in fog computing node

Before showing the proposed methodology, the accompanying definition [15] is given to the steady bit portrayal of every subsystem (5)- (6):

Definition 1 (SKR): Given a MIMO discrete-time LTI system G(z) in conditions (5)- (6), a stable direct system Ki is known as a steady bit portrayal (SKR) of Gi(z) if for any control input u(z) it fulfills

Ki [**uyii**((*zz*))] = **0***:*------------------- (1)

Hypothesis 1: Given a standard criticism control loop which comprises of a MIMO discrete-time LTI system Gi(z) in conditions (5)- (6) and an input controller Ki(z) in conditions (29)- (30), under the closed-loop presumptions that: the closed-loop is well-posed and internally stabilizedby **Ki**(*z*),

1) the closed-loop is very much presented and inside balanced out by Ki(z),
2) *sf ; sp* and *N* is sufficiently large such that **Zi c**;**d**;**N** = [$Z^{i}_{c;p;N}$ $M^{i}_{fT;N}$ Y_{fn}^{iT}; $]^{T}$ has full-row rank, then the thin LQ factorization:

$$\begin{bmatrix} Z^{i}_{c,p,N} \\ M^{i}_{f,N} \\ Y^{i}_{f,N} \end{bmatrix} = \underbrace{\begin{bmatrix} L^{i}_{c,11} & 0 & 0 \\ L^{i}_{c,21} & L^{i}_{c,22} & 0 \\ L^{i}_{c,31} & L^{i}_{c,32} & L^{i}_{c,33} \end{bmatrix}}_{L^{i}_{c}} \underbrace{\begin{bmatrix} Q^{i}_{c,1} \\ Q^{i}_{c,2} \\ Q^{i}_{c,3} \end{bmatrix}}_{Q^{i}_{c}}$$

is unique and a data-driven SKR of **Gi**(*z*) can be determined as:

$$\mathcal{K}^{i}_{d,s_f} = \Big[\underbrace{\mathcal{K}^{i}_{c,m,s_f}}_{\mathcal{K}^{i}_{d,u,s_f}} \quad \underbrace{\mathcal{K}^{i}_{c,y,s_f} + \mathcal{K}^{i}_{c,m,s_f} H^{i,c}_{u,s_f}}_{\mathcal{K}^{i}_{d,y,s_f}}\Big],$$

Where

$$\begin{bmatrix} \mathcal{K}^{i}_{c,m,s_f} & \mathcal{K}^{i}_{c,y,s_f} \end{bmatrix} \begin{bmatrix} L^{i}_{c,21} & L^{i}_{c,22} \\ L^{i}_{c,31} & L^{i}_{c,32} \end{bmatrix} = 0.$$

Moreover, Ki d;y;sf is the parity subspace of length sf of system Gi(z), i:e: Ki d;y;sf Γi sf = 0, and Ki d;u;sf =−Ki d;y;sf Hi u;sf .

B.Case Study on the TE bench mark system

In this segment, the proposed fog computing aided data-driven design methods are connected to the TE benchmark process. The process permits complete 52 estimations out of which 41 are process factors and 11 are controlled factors .Since TE process is very much concentrated in the writing, a concise depiction of the TE process is alluded to [30], [31] and excluded here. For our motivation, fog computing aided process monitoring system.

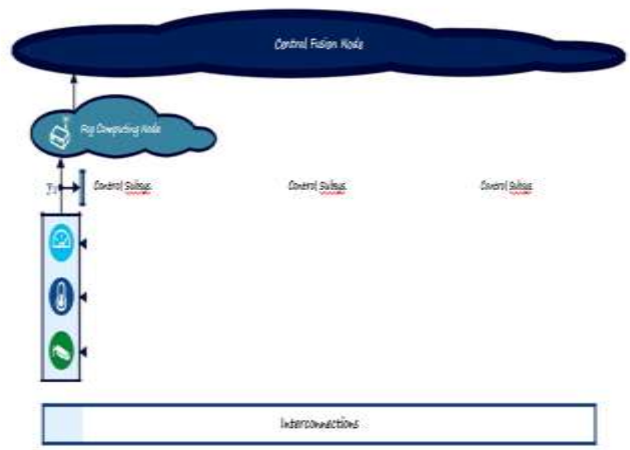

Fig. 2. The information exchange between fog computing nodes.

Designed for every subsystem, in particular reactor, condenser, blower, separator and stripper. In this segment, a blame of the response energy change, i:e: IDV(13), is considered. In every subsystem, the nearby controller Ki(z) has following structure:

$$u_{i,k} = K_{i,c}\left(e_{i,k} + \frac{T_{i,s}}{T_{i,i}} e_{i,k} - e_{i,k-1}\right),$$

where Ki;c, Ti;s and Ti;i are the controller parameters of subsystem I, and ei;k = !i;k − yi;k signifies the following mistake of subsystem I. In light of the proposed data-driven process monitoring approaches for each fog computing hub in Theorems 1, the accompanying test measurement can be embraced for the blame discovery reason:

$$J_{i,k} = \mathbf{r}_{\mathbf{all},\mathbf{i},k} \boldsymbol{\Sigma}^{-1}_{\mathbf{i},\mathbf{c}} \mathbf{r}_{\mathbf{all},\mathbf{i},k},$$

And the threshold is given by:

$$\boldsymbol{\Sigma}_{\mathbf{i},\mathbf{c}} = \frac{\mathcal{K}^{i}_{d,y,s_f} L^{i}_{c,33} (\mathcal{K}^{i}_{d,y,s_f} L^{i}_{c,33})^{\top}}{N-1}.$$

where $''_{i}$ is the significance level for *i*-th fog monitoring node and n^{i}_{K} is the dimension of the $r_{all;i;k}$.

The monitoring aftereffects of the proposed methodology are com-pared to the ones as per [32], in which the impacts of the controller on the process data are disregarded. Fig. 3-5 demonstrate the monitoring results on fog computing hubs of reactor and separator. All the more accurately, Fig. 3 demonstrates the monitoring results on fog computing hub for the reactor weight, where the controller parameters are given as Krp;c = −0:0001, Trp;s = 0:0005 and Trp;i = 0:3333. Fig. 6 demonstrates the monitoring results on fog computing hub for

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Available at https://journals.pen2print.org/index.php/ijr/
e-ISSN: 2348-6848
p-ISSN: 2348-795X
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the reactor temperature,

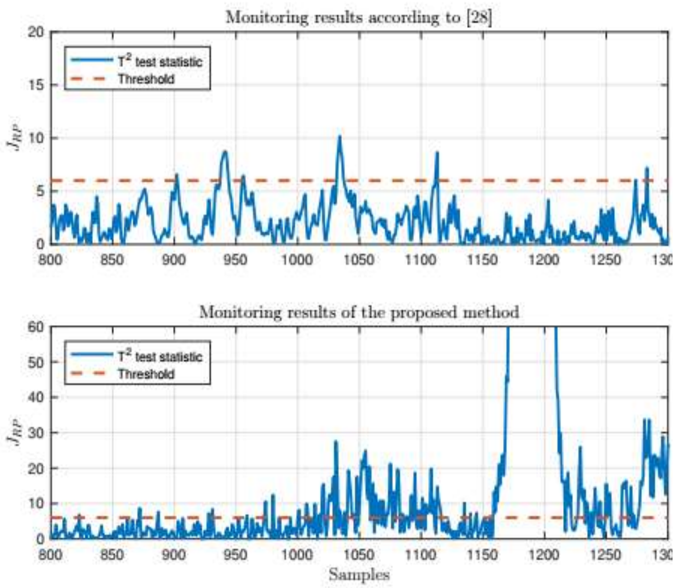

Fig. 3. Monitoring results on fog computing node for the reactor pressure.

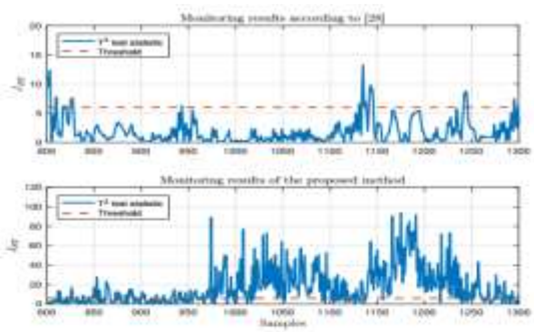

Fig. 4. Monitoring results on fog computing node for the reactor temperature.

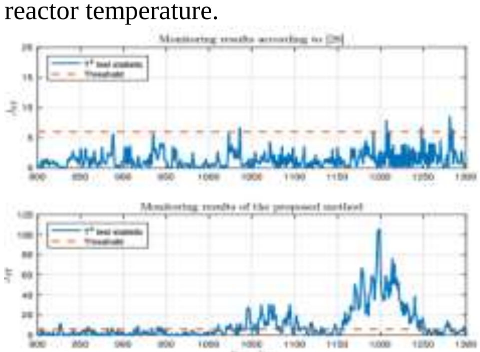

Fig. 5. Monitoring results on fog computing node for the separator temperature

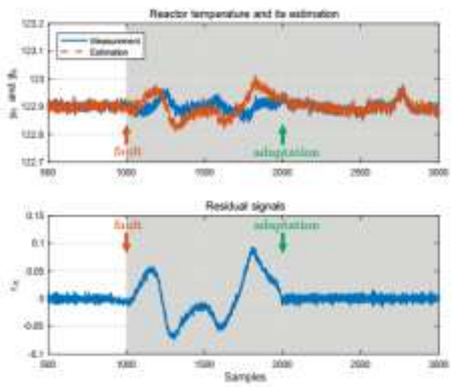

Fig. 6. Reactor temperature and its estimation befo re and after adaption

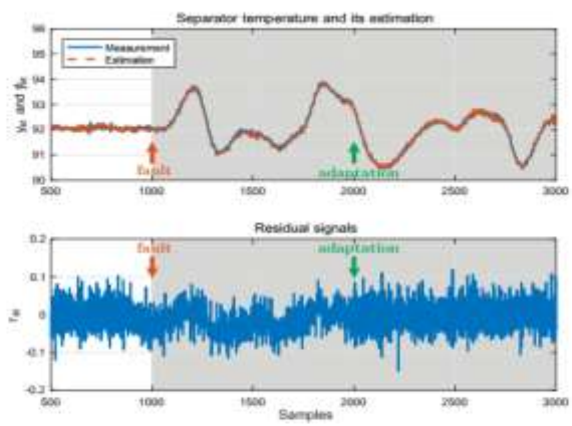

Fig. 7. Separator temperature and its estimation before and after adaption.

where the controller parameters are given as Krt;c = −8, Trt;s = 0:0005 and Trt;i = 0:1250. The monitoring results on fog computing hub for the separator temperature are given in Fig. 7, where the controller parameters are set to be Kst;c = −4, Tst;s = 0:0005 and Tst;i = 0:25. All monitoring outcomes are contrasted with the ones as indicated by [32]. Utilizing the blame free I/O data of every subsystem and the controller data, the data-driven SKR Kid;s in each fog computing hub can be recognized, and the monitoring system can be built. It is obvious from the correlations that the created methods give increasingly reliable and proficient monitoring results in each fog computing hub, in which the blame IDV(13) is thought to be showed up around 1000 inspecting moment

After the process change is distinguished, the adaptive configu-apportion approach ought to be enacted to catch the changed process elements. So as to demonstrate the effectiveness of the adaptive arrangement approach, the adjustment is enacted around 2000 examining moment. Fig. 7 demonstrates the deliberate re-on-screen character temperature and its estimation when adaption in reactor fog computing hub, where the ones of separator temperature are given in Fig. 6.

Since the blame under thought is IDV(13) which is the difference in response energy, it tends to be seen from Fig. 8 and 9 that this blame for the most part changes the elements of the reactor (incredibly influences the estimation of the reactor temperature) and effectsly affects the estimation of the separator temperature (the blame does not influence the elements of separator). After the adjustment, the difference in response energy has been caught/distinguished and the estimation begins to pursue the estimation (remaining progresses toward becoming around zeros) again in Fig. 7.

IV.CONCLUSION

In this paper, a fog computing aided process monitoring and control architecture is proposed for large-scale industrial processes. To adapt to the issues brought about by the progressions of process parameters and working focuses, a closed-loop data driven method is created for the process monitoring system design and an adaptive setup approach is proposed. The proposed fog computing aided process monitoring and control architecture adequately spares online computational burden and diminishes communicational endeavors, where the attainability and viability are confirmed and showed through the contextual analysis on the TE benchmark.

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