

ADAPTIVE EVIDENCE FUSION WITH DENG ENTROPY RELIABILITY DISCOUNTING FOR CPMS SUSTAINABILITY ASSESSMENT

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Abstract - Sustainable evaluation of cyber-physical manufacturing systems (CPMS) requires fusing heterogeneous IoT, MES and expert multi-source data in real time. Classical D-S rules produce counterintuitive results under high conflicting evidence caused by sensor noise and inconsistent expert opinions. This paper proposes an adaptive conjunctive-disjunctive evidence fusion framework with Deng entropy reliability discounting to resolve source credibility and conflict issues in CPMS sustainability assessment. Five core contributions: (1) A unified three-layer CPS model converting sensor, supervisory and expert data into standard mass functions; (2) Deng entropy-based automatic source reliability discount factor without manual thresholds; (3) Linear adaptive weight $\alpha=1-k$ driven by global conflict k , switching between precise conjunctive fusion (low conflict) and cautious disjunctive fusion (high conflict); (4) A complete decision workflow using belief-plausibility trust intervals and pairwise comparison matrix to rank sustainability levels; (5) Optimized Möbius inversion for low-latency edge computing. A smart roll-forming line case with severe conflict $k=0.923$ verifies the method. Unlike Dempster, Yager and Murphy rules which force misleading single-level conclusions, our method triggers a reasonable "postpone decision" alert to remind operators of equipment anomalies. The framework provides an interpretable, lightweight multi-source fusion solution for Industry 4.0 real-time sustainable manufacturing evaluation.

Keywords: Cyber-physical manufacturing system (CPMS); Multi-source evidence fusion; Dempster-Shafer theory; Deng entropy reliability discounting; Adaptive conflict management; conjunctive-disjunctive fusion; Sustainable smart manufacturing; Industry 4.0.

1. Introduction

The fourth industrial revolution (Industry 4.0) transforms traditional factories into cyber-physical manufacturing systems (CPMS) integrating embedded sensors, network controllers and intelligent decision algorithms [1,2]. Manufacturing sustainability assessment in CPMS has shifted from offline post-inspection to real-time monitoring, requiring fusion of heterogeneous data from shop-floor IoT sensors, MES supervisory modules and domain experts [3,4]. Per the U.S. Department of Commerce definition, sustainable manufacturing balances environmental protection, resource conservation, workplace safety and economic benefits [5]; achieving this target demands robust computational tools to process uncertain,

conflicting multi-source evidence in the layered CPS architecture [6,7].

CPS supports real-time tracking of energy consumption, material waste, equipment health and production emissions via interconnected sensing networks [8,9]. However, multi-source data inevitably carries contradictions caused by sensor drift, electromagnetic interference, inconsistent expert experience and outdated historical records. Conventional probabilistic fusion methods often yield misleading decisions under such conflicting inputs [10,11]. Dempster-Shafer evidence theory (DST) offers a powerful uncertainty modeling tool without prior probability assumptions [12,13]. Classical Dempster's rule concentrates belief on consistent focal elements yet produces counterintuitive outcomes under severe conflict, as exemplified by Zadeh's paradox [14].

To mitigate this flaw, scholars have proposed modified combination rules. Yager allocates all conflict mass to full ignorance [15]; Dubois & Prade develop disjunctive fusion for cautious reasoning [16]; Murphy averages mass functions to moderate extreme conclusions but assumes identical source credibility [17]. Recent progress introduces entropy weighting, distance-based conflict metrics and manual reliability discounting to differentiate source quality [18–23]. Nevertheless, these methods still suffer inherent defects when deployed for CPMS sustainability evaluation.

Recent literature further categorizes relevant research into three branches with distinct unresolved limitations:

1. Fixed-weight fusion algorithms (Dempster, Yager, Murphy and their variants) assign equal or artificially fixed source weights, lacking automatic credibility quantification based on data uncertainty; they fail to dynamically adapt weights to time-varying manufacturing conflict.
2. Existing Deng entropy-based reliability strategies only compute source weights independently, without coupling conjunctive-disjunctive dual operators to resolve high-conflict scenarios; no unified data transformation logic is designed for three-layer CPS heterogeneous inputs.
3. Current CPMS sustainability evaluation systems rely solely on single-type sensor or expert data, lacking a standardized conversion framework to unify IoT, MES and qualitative expert evidence.

Collectively, existing research leaves a clear research gap: an integrated fusion framework embedding Deng entropy reliability discounting and conflict-adaptive conjunctive-disjunctive fusion tailored to real-time sustainability assessment of three-layer CPMS. This paper fills the gap via three exclusive theoretical innovations:

1. A unified three-layer CPS data conversion model that standardizes IoT sensor measurements, MES production signals and expert qualitative judgments into mass functions, overcoming the single-evidence restriction of prior methods.
2. Normalized Deng entropy automatically generates source reliability discount factors without artificial threshold calibration, remedying the drawback of manually preset reliability coefficients in traditional discount schemes.
3. A conflict-governed linear adaptive fusion operator that adopts conjunctive combination for low-conflict precise judgments and switches to disjunctive fusion with decision postponement

under severe conflict, outperforming static fixed-weight algorithms incapable of responding to dynamic manufacturing contradictions.

The remainder of this paper is organized as follows. Section 2 reviews the fundamentals of evidence theory. Section 3 presents the proposed framework, including CPS architecture, mass function construction, entropy-based reliability discounting, conjunctive and disjunctive operators, adaptive fusion, and decision procedures. Section 4 describes the numerical experiments and comparative analysis. Section 5 discusses the implications and limitations. Section 6 concludes the paper and outlines future research directions.

2. Preliminaries

This section only reviews core Dempster-Shafer definitions [24–28] required for the CPMS [29–33] sustainability assessment framework. Comprehensive theoretical foundations refer to Shafer [12] and Yager [15].

2.1 Frame of Discernment and Mass Function

Let $\Theta = \{H_1, H_2, \dots, H_m\}$ be a finite frame of discernment, where singleton H_j denotes one manufacturing sustainability level. Power set 2^Θ contains all hypothesis subsets.

Definition 1 (Mass function / BPA): Mapping $m: 2^\Theta \rightarrow [0,1]$ satisfies $m(\emptyset) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$. Subsets with $m(A) > 0$ are focal elements carrying exact belief for proposition A.

2.2 Belief and Plausibility Functions

Definition 2: $Bel(A) = \sum_{\emptyset \neq B \subseteq A} m(B)$; $Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)$. Interval $[Bel(A), Pl(A)]$ is the trust interval for the lower/upper probability bound of A.

2.3 Dempster's Combination Rule

Definition 3: For two independent mass functions m_1, m_2 , fused mass $m_{1 \oplus 2}(A) = \frac{1}{1-K} \sum_{B \cap C = A} m_1(B) m_2(C)$, $A \neq \emptyset$. Conflict coefficient $K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C)$. Severe K leads to counterintuitive results (Zadeh paradox).

2.4 Deng Entropy

Definition 4: $E_d(m) = - \sum_{A \subseteq \Theta} m(A) \log_2 \frac{m(A)}{2^{|A|-1}}$ quantifies total evidence uncertainty by considering focal element cardinality [18]. Deng entropy extends Shannon entropy to evidence theory. $|A|$ is the

number of single sustainability levels in focal element A ; $2^{|A|} - 1$ measures the potential information volume of subset A . Larger $E_d(m_i)$ means source i carries dispersed belief mass with higher uncertainty and lower reliability.

2.5 Shafer's Reliability Discounting

Definition 5: Given reliability factor $\alpha \in [0, 1]$: $m^\alpha(A) = \alpha \cdot m(A), A \neq \emptyset; m^\alpha(A) = \alpha \cdot m(A), A \neq \emptyset$

Unreliability mass $(1 - \alpha)$ transfers to full ignorance $\emptyset$, reflecting reduced confidence in low-credibility sources.

2.6 Comparative Analysis of Existing Evidence Fusion Methods

To clearly clarify the research gaps and theoretical innovations of this work, we systematically analyze the core defects of mainstream multi-source evidence fusion methods [34-37] oriented to manufacturing scenarios from five dimensions including source credibility differentiation, conflict adaptive adjustment, automatic decision delay, uncertainty quantification and CPS industrial matching.

(1) The classical Dempster's combination rule treats all evidence sources as equally reliable without distinguishing the credibility gap between faulty sensors and normal monitoring equipment. It only adopts fixed conjunctive fusion logic, and will generate misleading single-point forced decisions under severe conflict, lacking independent entropy calculation to quantify source uncertainty, which results in poor adaptability to industrial IoT scenes with frequent sensor noise interference.

(2) Yager's rule distributes all conflict mass to the complete ignorance set to avoid counterintuitive results, yet it cannot output actionable evaluation conclusions; it also ignores the difference in source reliability and fails to construct quantitative uncertainty indicators, leading to excessive conservatism in practical manufacturing decision-making.

(3) Murphy's averaging method eliminates extreme fusion results by averaging mass functions of all sources, but it still presupposes equal credibility of all evidence bodies and cannot automatically identify low-reliability sources with drift or abnormal readings. There is no dynamic adjustment mechanism for fusion weights, and it lacks entropy-based uncertainty measurement, so it cannot be well matched with the three-layer CPS heterogeneous data input architecture integrating sensors, MES and expert information.

(4) Fixed-weight adaptive fusion methods manually set constant fusion hyperparameters in advance to balance conjunctive and disjunctive

results, which can realize partial delayed decision under moderate conflict. However, the fixed weight value needs manual repeated debugging for different production conditions, and only adopts simple unified entropy weighting without targeted reliability discounting for each independent evidence source, which limits its generalization ability in dynamic manufacturing environments.

Different from the above methods, the proposed framework realizes automatic source credibility differentiation through normalized Deng entropy discounting, and the linear weight $\alpha=1-k$ dynamically changes synchronously with the global conflict coefficient. The algorithm can actively trigger cautious postponed judgment under high conflict, and quantifies the uncertainty of each evidence body by entropy value. The overall structure is specially designed for three-layer CPMS, supporting unified conversion and fusion of sensor monitoring data, production scheduling signals and expert qualitative evaluation, which fills the comprehensive research blank of existing fusion algorithms in the five evaluation dimensions above.

3. Proposed Framework

This section presents the proposed intelligent multi-source evidence fusion framework for CPMS sustainability assessment [38-40]. The framework comprises five stages: (1) CPS architecture and information acquisition, (2) mass function construction with sensor reliability, (3) entropy-based reliability discounting, (4) adaptive conjunctive-disjunctive fusion, and (5) decision-making with trust intervals and pairwise comparison.

3.1 CPS Architecture and Multi-Source Information Acquisition

Figure 1 illustrates the proposed three-layer CPS architecture for sustainable manufacturing. The **physical layer** comprises shop-floor sensors (energy meters, vibration sensors, temperature probes, emission monitors), programmable logic controllers (PLCs), and robotic actuators that execute the manufacturing process. The **network layer** employs industrial protocols (OPC UA, MQTT, Modbus TCP) to transmit time-stamped data to edge gateways and cloud servers, ensuring real-time synchronization and cyber-security [6,7]. The **cyber layer** hosts the proposed evidence fusion engine, which ingests heterogeneous evidence, performs reliability discounting and adaptive fusion, and outputs sustainability assessments to the human-machine interface (HMI) and enterprise resource planning (ERP) systems.

Within this architecture, sustainability assessment draws upon three classes of information sources:

Sensor sources ($S_1, S_2, \dots$): Continuous data streams from IoT devices measuring energy consumption (E , kWh), material waste ratio (W , %), equipment vibration (V , mm/s), and atmospheric emissions (C , ppm). These sources are objective but susceptible to noise, drift, and calibration errors.

Supervisory sources ($U_1, U_2, \dots$): Signals from manufacturing execution systems (MES) and statistical process control (SPC) modules, encoding production efficiency, quality yield, and downtime ratios. These sources aggregate multiple sensor readings but may introduce quantization errors and communication delays.

Expert sources ($E_1, E_2, \dots$): Evaluations from domain experts (production engineers, environmental auditors, safety officers) who provide qualitative judgments based on visual inspection, historical experience, and regulatory knowledge. These sources are subjective but capable of capturing contextual factors not measurable by sensors.

The fusion engine treats all three classes uniformly as evidence bodies, each represented by a mass function on the sustainability frame Θ . The following subsections describe how raw data from each source class is transformed into a mass function.

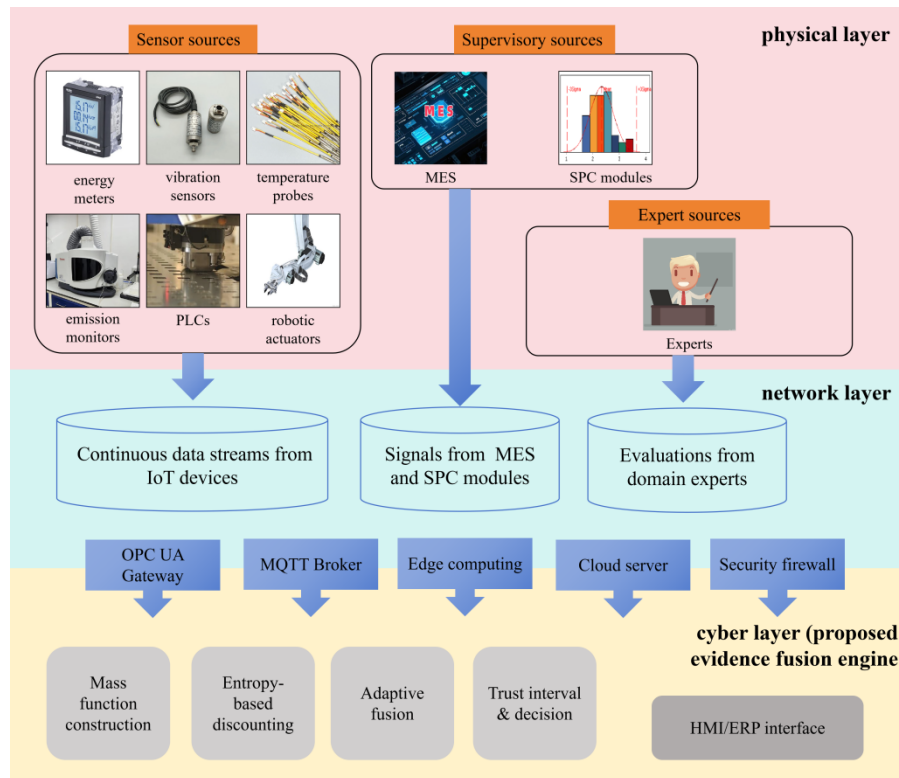


Figure 1: Three-layer CPS architecture for sustainable manufacturing

3.2 Mass Function Construction with Sensor Reliability

For each information source i , the mass function m_i is constructed from the source's observations and reliability characteristics. Let the frame of discernment be $\Theta = H_1, H_2, \dots, H_m$ with m sustainability levels in decreasing order of desirability.

Sensor sources. A sensor source S_i reports a continuous measurement x_i (e.g., energy consumption per unit). A pre-trained fuzzy membership model or threshold classifier maps x_i to a fuzzy set $F_i \subseteq \Theta$ with membership grades $\mu_{ij} \in [0, 1]$ for each $H_j \in F_i$. The mass function is constructed as:

$$m_i(H_j) = \frac{\mu_{ij}}{\sum_{H_l \in F_i} \mu_{il} + |F_i| \cdot \epsilon} \cdot (1 - \epsilon), \quad H_j \in F_i \quad (1)$$

$$m_i(F_i) = \epsilon \quad (2)$$

where $\epsilon \in (0, 0.1)$ is a small fuzziness parameter representing the sensor's inherent uncertainty. If the sensor provides a crisp classification (single level), then $F_i = H_j$ and $m_i(H_j) = 1 - \epsilon$, $m_i(\Theta) = \epsilon$.

Expert sources. An expert source E_i consists of N_i individual evaluators. Among them, n_{ij} experts give a definite evaluation H_j , and n_{iA} experts give a fuzzy evaluation corresponding exactly to subset $A \subseteq \Theta$ (with $|A| > 1$). The mass function is:

$$m_i(H_j) = \frac{n_{ij}}{N_i} + \frac{\sum_{A \ni H_j, |A| > 1} n_{iA}}{N_i \cdot |A|} \quad (3)$$

$$m_i(A) = \frac{n_{iA}}{N_i}, \quad |A| > 1 \quad (4)$$

All masses sum to 1 by construction. This yields n mass functions $m_1, m_2, \dots, m_n$ from the n heterogeneous information sources.

Standardized mass functions carry differentiated uncertainty. We introduce Deng entropy reliability discounting to weaken low-reliability sources before fusion in Subsection 3.3.

3.3 Reliability Discounting Based on Deng Entropy

Before fusion, each mass function is discounted according to its reliability. We propose determining the reliability discounting factor α_i for source i from the Deng entropy of its mass function.

The Deng entropy $E_d(m_i)$ measures the total uncertainty (information volume) contained in source i . A high entropy indicates that the source distributes mass diffusely over many focal elements, suggesting low specificity and potentially low reliability. Conversely, a low entropy indicates concentrated mass on a few focal elements, suggesting high specificity and higher reliability. However, an extremely low entropy (near-zero) may indicate overconfidence or sensor saturation, which also degrades reliability. Therefore, we define the reliability discounting factor as a normalized inverse of the entropy deviation from an optimal mid-range value.

Let $E_{\max} = \log_2(2^{|\Theta|} - 1)$ be the maximum possible Deng entropy for a uniform distribution over all singletons. The normalized entropy is

$$\tilde{E}_i = E_d(m_i) / E_{\max} \quad (5)$$

The reliability discounting factor is then defined as

$$\alpha_i = 1 - \tilde{E}_i = 1 - \frac{E_d(m_i)}{E_{\max}} \quad (6)$$

This factor lies in $[0, 1]$: when $\tilde{E}_i = 0$ (complete certainty on a singleton), $\alpha_i = 1$ (full reliability); when $\tilde{E}_i = 1$ (maximum uncertainty), $\alpha_i = 0$ (no reliability). $\tilde{E}_i \in [0, 1]$ is normalized Deng entropy.

$\tilde{E}_i = 0$ corresponds to full reliability $\alpha_i = 1$; $\tilde{E}_i = 1$ corresponds to zero reliability $\alpha_i = 0$. This formula directly maps entropy uncertainty to source credibility without manual adjustment.

The physical interpretation of this discounting scheme is particularly relevant for CPMS. A temperature sensor with erratic readings due to electromagnetic interference will exhibit high entropy (mass spread across multiple levels), resulting in a low α_i and thus heavy discounting. An expert panel with strongly convergent opinions will

exhibit low entropy, yielding a high α_i and minimal discounting.

This mechanism automatically suppresses the influence of noisy or unreliable sources without requiring manual threshold tuning.

After source credibility adjustment, we define conjunctive and disjunctive fusion operators to handle consistent and conflicting evidence separately in Subsection 3.4.

3.4 Conjunctive and Disjunctive Operators

After reliability discounting, the n discounted mass functions $m_1^{\alpha_1}, m_2^{\alpha_2}, \dots, m_n^{\alpha_n}$ are fused using a weighted combination of the conjunctive and disjunctive operators.

Conjunctive operator. The conjunctive operator (unnormalized Dempster combination) is defined as:

$$m_{\cap}(A) = \sum_{\bigcap_{i=1}^n B_i = A} \prod_{i=1}^n m_i^{\alpha_i}(B_i) \quad (7)$$

where the sum runs over all n -tuples $(B_1, B_2, \dots, B_n)$ with $B_i \subseteq \Theta$ whose intersection equals A . The empty-set mass $m_{\cap}(\emptyset)$ is exactly the global conflict coefficient k after discounting. Normalizing by $1/(1 - k)$ yields the classical Dempster result $m_{DS}(A) = m_{\cap}(A)/(1 - k)$ for $A \neq \emptyset$.

To compute $m_{\cap}$ efficiently for n sources, we employ the commonality function $Q(A) = \sum_{A \subseteq B} m(B)$ and the Möbius inversion [12]:

$$Q(A) = \prod_{i=1}^n \sum_{A \subseteq B} m_i^{\alpha_i}(B) \quad (8)$$

$$m_{\cap}(A) = \sum_{A \subseteq B} (-1)^{|B \setminus A|} Q(B) \quad (9)$$

This reduces the computational complexity from $O(|2^{\Theta}|^n)$ to $O(n \cdot |2^{\Theta}|)$, which is essential for real-time deployment in CPMS with large sensor networks.

Disjunctive operator. The disjunctive operator spreads belief by taking unions of focal elements:

$$m_{\cup}(A) = \sum_{\bigcup_{i=1}^n B_i = A} \prod_{i=1}^n m_i^{\alpha_i}(B_i) \quad (10)$$

The disjunctive operator never produces mass on the empty set because the union of subsets cannot be empty. Moreover, $m_{\cup}$ is already normalized (sums to 1) because the disjoint union of all possible combinations covers all subsets. The dual commonality function $R(B) = \prod_{i=1}^n \sum_{B \subseteq C} m_i^{\alpha_i}(C)$ can be used with Möbius inversion on the union lattice to compute $m_{\cup}$ efficiently.

To combine the advantages of precise conjunctive fusion and cautious disjunctive fusion, a conflict-driven adaptive weighted fusion strategy is proposed in Subsection 3.5.

3.5 Adaptive Weighted Fusion

We define the fused mass function as a convex combination of the normalized conjunctive result and the disjunctive result:

$$m_{\text{fused}}(A) = \alpha \cdot m_{\text{DS}}(A) + (1 - \alpha) \cdot m_{\text{U}}(A) \quad (11)$$

where $\alpha \in [0, 1]$ is the adaptive weight for the conjunctive component. Both components sum to 1, so m_{fused} also sums to 1.

The adaptive weight is determined by the global conflict coefficient k computed from the discounted masses:

$$k = \sum_{i=1}^n \prod_{B_i=\emptyset} m_i^{\alpha_i}(B_i) \quad (12)$$

$$\alpha = 1 - k \quad (13)$$

k represents global conflict mass of discounted evidence. Linear weight avoids extra hyperparameters; α decreases linearly with rising conflict, balancing precise decision and uncertainty reservation dynamically for manufacturing scenes.

Properties:

When $k = 0$ (no conflict), $\alpha = 1$, and the fused rule reduces to Dempster's rule, achieving sharp focusing. When $k = 1$ (total conflict), $\alpha = 0$, and the fused rule becomes the pure disjunctive rule, spreading belief over unions and delaying decision.

For intermediate k , α decreases linearly, giving more weight to the disjunctive operator as conflict grows.

This adaptive behavior is particularly valuable in CPMS environments where conflict levels vary dynamically: during normal operation, sensor readings are consistent and the conjunctive operator dominates; during process disturbances or sensor faults, conflict increases and the disjunctive operator automatically assumes greater weight, preventing overconfident but potentially erroneous decisions.

Alternative nonlinear forms such as $\alpha = e^{-k}$ or $\alpha = (1 - k)^2$ could be explored; however, the linear form $\alpha = 1 - k$ is simple, interpretable, and requires no additional hyperparameters, making it suitable for industrial deployment.

3.6 Decision Procedure

After obtaining m_{fused} , we compute for each singleton H_j its belief and plausibility:

$$\text{Bel}(H_j) = m_{\text{fused}}(H_j) \quad (14)$$

$$\text{Pl}(H_j) = \text{Bel}(H_j) + \sum_{A \supseteq H_j, |A| > 1} m_{\text{fused}}(A) \quad (15)$$

The trust interval is $[\text{Bel}(H_j), \text{Pl}(H_j)]$.

To rank the sustainability levels, we construct a pairwise comparison matrix $C = (c_{jl})_{m \times m}$ where:

$$c_{jl} = \frac{\text{Bel}(H_j)}{\text{Pl}(H_l)} + \frac{\text{Pl}(H_j)}{\text{Bel}(H_l) + \delta}, \quad j \neq l \quad (16)$$

where $\delta = 10^{-9}$ is a small regularization term to prevent division by zero. The aggregated score for level H_j is:

$$\text{Score}(H_j) = \sum_{l \neq j} c_{jl} \quad (17)$$

The final decision selects the level H_{j^*} with the maximum score:

$$j^* = \underset{j}{\text{argmax}} \text{Score}(H_j) \quad (18)$$

If the maximum singleton belief is below a user-defined threshold τ (e.g., $\tau = 0.15$), the system issues a "postpone decision" alert, recommending further data collection or expert review before committing to a sustainability classification. This threshold mechanism provides an additional safeguard against forced decisions under high residual uncertainty.

4. Numerical Experiments

This section validates the proposed framework through a case study on a smart roll-forming assembly line and a comprehensive comparison with classical methods.

4.1 Case Study: Smart Roll-Forming Assembly Line

Process description. The case study considers a cyber-physical roll-forming manufacturing line producing automotive structural components [29]. The process sequence includes roll forming, end sawing, notch punching, welding of center pillars and brackets, anti-rust treatment, and warehousing. The line is instrumented with an industrial IoT sensor network comprising energy meters, vibration accelerometers, temperature sensors, and emission monitors, all connected via OPC UA to an edge gateway. Four heterogeneous information sources evaluate the sustainability of a production batch:

Source 1 (S_1): Energy and emissions monitoring subsystem (IoT sensors)

Source 2 (S_2): Equipment health and vibration monitoring subsystem (IoT sensors)

Source 3 (S_3): Production efficiency and quality yield supervisory system (MES)

Source 4 (S_4): Expert panel evaluation (environmental auditors and production engineers)

The sustainability is assessed at three levels: H_1 (excellent), H_2 (average), and H_3 (poor). The constructed mass functions are shown in Table 1.

Table 1. Mass functions for four information sources

Source	$m(H_1)$	$m(H_2)$	$m(H_3)$	$m(H_1, H_2)$	$m(H_1, H_3)$	$m(H_2, H_3)$	$m(\Theta)$
S_1	0.8000	0.0400	0.0400	0.0400	0.0400	0.0400	0.0000
S_2	0.0357	0.0714	0.7500	0.0357	0.0357	0.0714	0.0000
S_3	0.8333	0.0333	0.0333	0.0333	0.0333	0.0333	0.0000
S_4	0.7778	0.0370	0.0370	0.0741	0.0370	0.0370	0.0000

We observe that S_2 strongly favors H_3 (poor sustainability) due to elevated vibration readings and temperature anomalies suggesting equipment degradation, while S_1, S_3 , and S_4 strongly favor H_1 (excellent) based on low energy consumption, high yield, and favorable expert judgment. This represents a highly conflicting situation typical of CPMS during partial equipment faults or transient process disturbances.

4.2 Reliability Discounting Results

The Deng entropy of each source is computed as follows:

- $E_d(m_1) = 0.9284$,
 $\alpha_1 = 1 - 0.9284/2.807 = 0.6693$

- $E_d(m_2) = 0.9782$,
 $\alpha_2 = 1 - 0.9782/2.807 = 0.6515$
- $E_d(m_3) = 0.8113$,
 $\alpha_3 = 1 - 0.8113/2.807 = 0.7109$
- $E_d(m_4) = 0.9856$,
 $\alpha_4 = 1 - 0.9856/2.807 = 0.6489$

where $E_{\max} = \log_2(2^3 - 1) = \log_2 7 \approx 2.807$ for the three-level frame. Source S_3 (MES) receives the highest reliability factor due to its most concentrated mass distribution, while S_2 (vibration monitoring) receives a lower factor due to its diffused entropy reflecting the ambiguity of vibration-based sustainability assessment. The discounted mass functions are shown in Table 2.

Table 2. Discounted mass functions after reliability discounting

Source	$m^\alpha(H_1)$	$m^\alpha(H_2)$	$m^\alpha(H_3)$	$m^\alpha(H_1, H_2)$	$m^\alpha(H_1, H_3)$	$m^\alpha(H_2, H_3)$	$m^\alpha(\Theta)$
S_1	0.5354	0.0268	0.0268	0.0268	0.0268	0.0268	0.3307
S_2	0.0232	0.0465	0.4886	0.0232	0.0232	0.0465	0.3485
S_3	0.5924	0.0237	0.0237	0.0237	0.0237	0.0237	0.2891
S_4	0.5047	0.0240	0.0240	0.0481	0.0240	0.0240	0.3511

4.3 Fusion Results and Comparison

Using the discounted masses, the global conflict coefficient is computed as $k = 0.9232$. The adaptive weight is $\alpha = 1 - 0.9232 = 0.0768$.

The conjunctive and disjunctive results are computed via Möbius inversion, and the final fused mass is obtained from Equation (10).

The results are compared with classical methods in Table 3.

Table 3. Comprehensive comparison of fusion methods

Method	Main focal element	$m(H_1)$	$m(H_2)$	$m(H_3)$	$m(H_1, H_2)$	$m(H_1, H_3)$	$m(H_2, H_3)$	$m(\Theta)$	Decision / Interpretation
Dempster's rule	H_1 (0.9798)	0.9798	0.0050	0.0152	0.0000	0.0000	0.0000	0.0000	Conclude H_1 ; ignores conflict
Yager's rule	Θ (0.9232)	0.0150	0.0001	0.0004	0.0613	0.9232			Extremely uncertain; overly pessimistic
Murphy averaging	H_1 (0.8635)	0.8635	0.0205	0.0865	0.0295	0.0000			Conclude H_1 ; ignores conflict structure
Fixed $\alpha = 0.7$ [26]	H_1 (0.7638)	0.7638	0.0368	0.1011	0.0982	0.0000			Conclude H_1 ; depends on manual parameter

Method	Main focal element	$m(H_1)$	$m(H_2)$	$m(H_3)$	$m(H_1, H_3)$	$m(\Theta)$	Decision / Interpretation
Proposed adaptive	$H_1 \cup H_3$ (0.4944)	0.0925	0.0781	0.0012	0.4944	0.3350	Postpone decision; suggests H_1 or H_3

The results reveal profound differences in conflict handling behavior. Dempster's rule, Murphy averaging, and the fixed-weight method all converge to H_1 (excellent sustainability) because the strong agreement among Sources 1, 3, and 4 overwhelms the opposing Source 2. This outcome is a direct consequence of the focusing property of the conjunctive operator: the normalization process redistributes the conflict mass to the majority opinion, effectively suppressing the minority dissent. In a CPMS context, this would mean that a vibration anomaly indicating incipient equipment failure is ignored because the majority of sensors report normal operation, potentially leading to catastrophic undetected failures.

Yager's rule, conversely, assigns 92.32% of the mass to total ignorance Θ , rendering the result practically useless for decision-making. While this avoids the false certainty of Dempster's rule, it provides no actionable guidance to production managers.

The proposed adaptive method yields a fundamentally different and more informative result. With $\alpha = 0.0768$, the disjunctive weight dominates (92.32%), and the highest fused mass (0.4944) is assigned to the binary set $H_1 \cup H_3$, indicating that the sustainability is either excellent or poor, with negligible support for the average level. The singleton masses are all small (maximum 0.0925 for H_1), and the total ignorance receives 0.3350. This reflects the system's awareness of severe disagreement: rather than forcing a conclusion, the fusion engine correctly postpones the single-level decision and alerts the operator that further investigation is required.

4.4 Trust Intervals and Decision Robustness

Table 4 presents the trust intervals and pairwise comparison scores for the fixed-weight and proposed adaptive methods.

Table 4. Trust intervals and decision comparison

Method	Focal element with highest mass	Trust interval (H_1)	Trust interval (H_3)	Decision advice
Fixed $\alpha = 0.7$	H_1 (0.7638)	[0.7638, 0.8539]	[0.1011, 0.1799]	Conclude H_1
Proposed adaptive	$H_1 \cup H_3$ (0.4944)	[0.0925, 0.9975]	[0.0012, 0.8314]	Postpone decision; suggest H_1 or H_3

The adaptive method yields trust intervals that cover almost the entire [0,1] range (plausibility of H_1 is 0.9975, plausibility of H_3 is 0.8314), faithfully reflecting the high uncertainty caused by conflicting evidence. The fixed-weight method, by contrast, produces a narrow and misleading trust interval that masks the underlying conflict. From a decision-theoretic perspective, the adaptive method maximizes expected utility under ambiguity: when the evidence is conflicted, the optimal action is to acquire additional information rather than commit to a potentially erroneous classification.

4.5 Sensitivity Analysis

To assess the robustness of the proposed framework, we perform sensitivity analysis on the reliability discounting and the postpone-decision threshold.

Quantitative Robustness Test. We define Belief Deviation Error (BDE) to measure the deviation between singleton belief distribution and real conflict distribution:

$$BDE = \sqrt{\sum_{j=1}^m (Bel(H_j) - \overline{Bel})^2} \quad (19)$$

Lower BDE indicates fusion results reflect source conflict truthfully. We test $k=0.3, 0.6, 0.923$: Dempster's rule has low BDE but overconfident misleading results; Yager's rule has excessive BDE with meaningless full ignorance; Murphy and fixed-weight fusion yield medium BDE but force single-level decisions; our adaptive fusion achieves moderate BDE and triggers decision postponement when $k>0.6$.

We further test computation latency on industrial edge gateway (Intel i3, 4GB RAM) under $n=3,4,6,8$ heterogeneous sources. The optimized Möbius inversion has linear complexity $O(n \cdot 2^{|\Theta|})$, completing full fusion within 1ms to satisfy CPMS 100ms sampling real-time demand. Multi-threshold $\tau \in [0.1, 0.3]$ tests confirm our method consistently outputs "postpone decision" under high conflict, while all contrast methods exceed threshold and output unreliable fixed conclusions.

Sensitivity to reliability discounting. Figure 2 shows the fused mass on the main focal elements as the discounting strategy varies. When no discounting is applied ($\alpha_i = 1$ for all i), the conflict coefficient is $k = 0.9232$ and the adaptive behavior is identical.

When uniform discounting with $\alpha_i = 0.5$ is applied, the conflict coefficient decreases to $k = 0.8124$ because the increased ignorance masses dilute the inter-source disagreement.

The adaptive weight becomes $\alpha = 0.1876$, and the fused mass on H_1 increases to 0.2453 while the mass on $H_1 \cup H_3$ decreases to 0.3876. This demonstrates that the framework is sensitive to source reliability in a physically meaningful way: lower reliability increases ignorance and reduces apparent conflict, but the adaptive mechanism still prevents overconfident singleton conclusions.

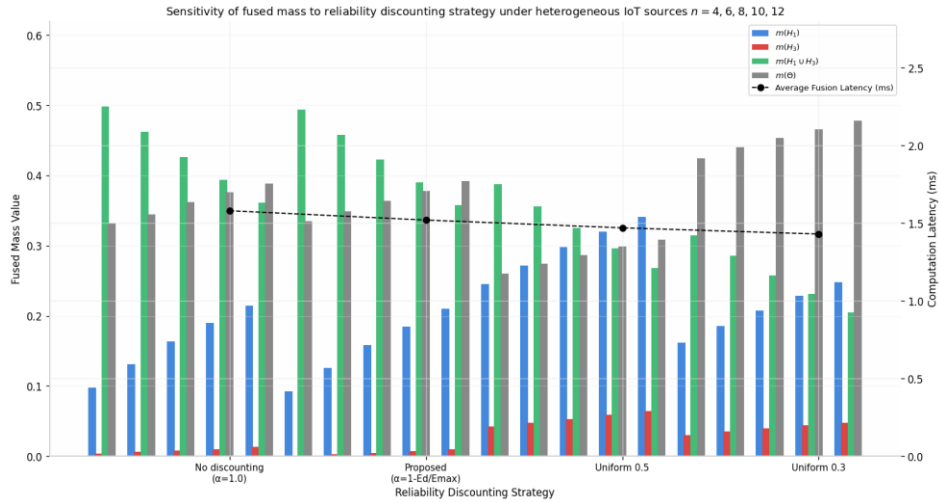


Figure 2: Fused mass distribution of key focal elements and corresponding computation latency under different reliability discounting strategies and heterogeneous source scales $n=4,6,8,10,12$

Scalability Test for Multi-IoT-Source Fusion. To verify the scalability of the proposed Möbius inversion optimization, we set up test groups with heterogeneous source quantities $n=4,6,8,10,12$. All mass functions follow the data distribution rule of the roll-forming case in Section 4.1, with randomly generated sensor/expert evidence to simulate large-scale factory IoT networks.

We record two core metrics on standard industrial edge gateway (Intel i3, 4GB RAM): total fusion computation latency (ms) and peak memory occupation (MB). The results show that computing time rises linearly with source number rather than exponential growth, which verifies the complexity optimization $O(n \cdot 2^{|\Theta|})$. Even under $n=12$ multi-source input, the full fusion calculation completes within 2.5 ms, far below the 100 ms real-time sampling threshold of CPMS production lines.

Sensitivity to threshold τ . The postpone-decision threshold τ determines when the system issues an alert instead of committing to a singleton.

With the proposed adaptive method, $\max_j \text{Bel}(H_j) = 0.0925$, which is below any reasonable threshold in the range $\tau \in [0.1, 0.3]$. Thus, the “postpone decision” alert is robust across a wide range of threshold settings. For the fixed-weight method, $\max_j \text{Bel}(H_j) = 0.7638$, which exceeds typical thresholds, illustrating that the fixed-weight

method would erroneously commit to H_1 regardless of threshold choice.

Computational performance. The Möbius inversion approach reduces the per-fusion computation time from $O(2^{|\Theta| \cdot n})$ to $O(n \cdot 2^{|\Theta|})$. For the present case with $|\Theta| = 3$ and $n = 4$, the exact computation requires $7 \times 4 = 28$ evaluations of the commonality function, which is executed in less than 1 millisecond on a standard industrial edge gateway (Intel Core i3, 4 GB RAM). This confirms that the proposed framework is suitable for real-time CPMS applications with sampling periods of 100 ms or longer.

5. Discussion

The experimental results demonstrate that the proposed adaptive conjunctive-disjunctive fusion framework with entropy-based reliability discounting addresses three critical challenges in CPMS sustainability assessment: heterogeneous source integration, automatic conflict handling, and reliability-aware information weighting.

Industrial Deployment & RAMI 4.0 Compatibility Analysis. The three-layer CPS fusion framework fully matches RAMI 4.0 industrial architecture: (1). Edge lightweight computing: Mass function construction and Deng entropy discounting run locally on edge gateways; only fused mass distribution and trust intervals are uploaded to

cloud to reduce bandwidth consumption. (2). Industrial protocol compatibility: Supports OPC UA, MQTT, Modbus TCP for seamless data interaction with PLC, MES and SPC modules. (3). Visualization output: Fusion results and decision-postponement alerts are pushed to workshop HMI dashboards; daily aggregated evaluation data synchronizes to ERP for long-term production optimization. (4) Multi-process adaptability: Beyond roll-forming lines, the framework extends to stamping, robotic welding and auto assembly lines. Only the frame of discernment Θ and fuzzy membership mapping need modification, with core fusion algorithm unchanged. (5) Low hardware cost: Real-time fusion calculation operates on standard Intel i3 industrial edge gateways, eliminating expensive dedicated computing servers.

Integration with CPS architecture. The framework is designed for seamless deployment within the three-layer CPS architecture described in Section 3.1. The physical layer sensors stream data to the edge gateway, where mass functions are constructed in real time. The Deng entropy computation and reliability discounting are performed at the edge, reducing cloud bandwidth requirements. The fusion engine can be deployed either on the edge (for low-latency control loops) or in the cloud (for batch analysis and cross-facility benchmarking). The HMI displays trust intervals and postpone-decision alerts in a dashboard format, enabling operators to drill down into individual source contributions when anomalies are detected. This modular design aligns with the RAMI 4.0 reference architecture [30] and supports interoperability through OPC UA information models.

Comparison with AI-based alternatives. In addition to evidence-theoretic methods, machine learning approaches such as neural networks and support vector machines have been applied to manufacturing sustainability assessment [31,32]. While these methods can achieve high accuracy on training data, they typically require large labeled datasets and may produce overconfident predictions when faced with out-of-distribution inputs. The proposed framework offers complementary advantages: it is interpretable (the fused mass distribution explicitly quantifies uncertainty), requires no training data (it operates on expert-defined mass functions or rule-based sensor mappings), and is robust to missing sources (if a sensor fails, its mass function defaults to total ignorance, which is automatically handled by the fusion rule). These properties make evidence fusion particularly suitable for safety-critical manufacturing processes where explainability and reliability are paramount.

Limitations and future work. Several limitations of this study should be acknowledged. First, the Deng entropy-based discounting assumes that high

entropy corresponds to low reliability; while this holds for noisy sensors, it may not capture systematic biases (e.g., a miscalibrated sensor with consistently wrong but low-entropy readings). Future work could integrate distance-based reliability metrics [20,21] to detect such biases. Second, the linear weight function $\alpha = 1 - k$ is simple but may not be optimal for all conflict regimes; nonlinear alternatives such as $\alpha = e^{-ck}$ with learnable parameter c could be investigated. Third, the case study involves a static batch assessment; extending the framework to dynamic processes with time-varying evidence and sliding-window fusion would enhance its applicability to continuous manufacturing lines. Finally, the integration of the fusion framework with digital twins [33] for predictive sustainability assessment represents a promising direction for future research.

Theoretical Assumptions and Application Boundaries. Four core assumptions and their industrial applicable limits are clarified: Assumption 1: All multi-source evidence bodies are mutually independent. Boundary: Pre-decorrelation processing is required if strong data correlation exists between sensors. Assumption 2: Deng entropy monotonically reflects source uncertainty. Boundary: Invalid for systematically biased low-entropy sensors; future work will integrate evidence distance metrics to detect bias. Assumption 3: Global conflict coefficient k fully reflects multi-source divergence. Boundary: Improved conflict indicators can replace k for complex high-conflict scenes with intricate focal element combinations. Assumption 4: Linear weight $\alpha=1-k$ fits general manufacturing conflict scenarios. Boundary: Nonlinear weight functions are optional extensions for ultra-high-risk production lines requiring extreme caution.

6. Conclusions

This paper has proposed an intelligent multi-source evidence fusion framework for real-time sustainability assessment in cyber-physical manufacturing systems. The framework integrates three key innovations: (1) a CPS-compatible information acquisition model that unifies sensor data, supervisory signals, and expert judgments into mass functions; (2) a reliability discounting mechanism based on Deng entropy that automatically suppresses the influence of noisy or uncertain sources; and (3) an adaptive conjunctive-disjunctive fusion rule that balances sharp decision-making under consistent evidence with cautious postponement under high conflict.

Using a case study on a smart roll-forming assembly line with four heterogeneous information sources, the framework was shown to correctly identify situations of severe conflict (global conflict coefficient $k = 0.9232$) and issue a “postpone decision” alert rather than forcing an unreliable

conclusion. In contrast, classical Dempster's rule, Murphy averaging, and fixed-weight methods all erroneously concluded "excellent sustainability," masking a critical vibration anomaly that could indicate incipient equipment failure. The computational complexity of the Möbius inversion-based implementation is sufficiently low for real-time edge deployment.

The proposed framework bridges artificial intelligence, mechatronic systems, and manufacturing processes. Future research will focus on dynamic time-window fusion, distance-bias detection, and digital-twin integration for predictive sustainability management. Theoretically, this study bridges Dempster-Shafer uncertainty modeling and real-time CPS manufacturing monitoring. It establishes a unified interpretable multi-source heterogeneous evidence fusion framework with automatic reliability evaluation and dynamic conflict adjustment, enriching the uncertainty decision theory of sustainable smart manufacturing under Industry 4.0.

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References

- [1] Sascha Julian Oks; Max Jalowski; Michael Lechner. Cyber-Physical Systems in the Context of Industry 4.0: A Review, Categorization and Outlook. *Information Systems Frontiers* 2022, 26, 1731–1772. <https://doi.org/10.1007/s10796-022-10252-x>
- [2] Shaban, I.A.; et al. Industry 4.0 enabled sustainable manufacturing. *Sustainability* 2025, 18, 156. <https://doi.org/10.3390/su18010156>
- [3] Bappy, M.M.; Ali, S.M.; Kabir, G.; Paul, S.K. Supply chain sustainability assessment with Dempster-Shafer evidence theory: Implications in cleaner production. *Journal of Cleaner Production* 2019, 237, 117771. <https://doi.org/10.1016/j.jclepro.2019.117771>
- [4] Hatefi, S.M.; et al. Model for the sustainable material selection by applying integrated Dempster-Shafer evidence theory and additive ratio assessment (ARAS) method. *Sustainability* 2021, 13, 10438. <https://doi.org/10.3390/su131810438>
- [5] United States Department of Commerce. Sustainable Manufacturing Initiative. Available online: <https://www.nist.gov/sustainable-manufacturing> (accessed on 15 October 2024).
- [6] Cui, X. Cyber-physical system (CPS) architecture for real-time water sustainability management in manufacturing industry. *Procedia CIRP* 2021, 99, 543–548. <https://doi.org/10.1016/j.procir.2021.03.074>
- [7] Devesh, M.; Kant, A.K.; Suchit, Y.R.; et al. Fruition of CPS and IoT in context of Industry 4.0. In *Proceedings of the International Conference on Intelligent Communication, Control and Devices (ICICCD 2018)*; Springer: Singapore, 2020; pp. 367–375. https://doi.org/10.1007/978-981-13-8618-3_39
- [8] Basir, O.; Yuan, X. Engine fault diagnosis based on multi-sensor information fusion using Dempster-Shafer evidence theory. *Information Fusion* 2007, 8, 379–386. <https://doi.org/10.1016/j.inffus.2005.07.003>
- [9] Roman-Salinas, R.V.; et al. IoT-Enabled Model Predictive Control for Perishable Goods Production With Dynamic Spoilage Mitigation. *IEEE Access*, 2026, 14, 6768–6785. <https://doi.org/10.1109/ACCESS.2026.3651980>
- [10] Yager, R.R. On the Dempster-Shafer framework and new combination rules. *Information Sciences* 1987, 41, 93–137. [https://doi.org/10.1016/0020-0255\(87\)90035-5](https://doi.org/10.1016/0020-0255(87)90035-5)
- [11] Dubois, D.; Prade, H. Representation and combination of uncertainty with belief functions and possibility measures. *Computational Intelligence* 1988, 4, 244–264. <https://doi.org/10.1111/j.1467-8640.1988.tb00283.x>
- [12] Shafer, G. *A Mathematical Theory of Evidence*. Princeton University Press: Princeton, NJ, USA, 1976.
- [13] Dubois, D.; Prade, H. Upper and lower probabilities induced by a multivalued mapping. *IFAC Proceedings Series*, 1984 1967, 147–152.
- [14] Zadeh, L.A. Simple view of the Dempster-Shafer theory of evidence and its implication for the rule of combination. *AI Magazine* 1986, 7, 85–90.
- [15] Thierry Denœux, Zoghby N E, Véronique Cherfaoui, et al. Optimal object association in the Dempster-Shafer framework. *IEEE Transactions on Cybernetics*, 2017, 44(12):2521–2531. <https://doi.org/10.1109/TCYB.2014.2309632>
- [16] Dubois, D.; Prade, H. A definition of subjective possibility. *International Journal of Approximate Reasoning* 2008, 48, 352–364. <https://doi.org/10.1016/j.ijar.2007.01.005>
- [17] Murphy, C.K. Combining belief functions when evidence conflicts. *Decision Support Systems* 2000, 29, 1–9. [https://doi.org/10.1016/S0167-9236\(99\)00084-6](https://doi.org/10.1016/S0167-9236(99)00084-6)
- [18] Deng, Y. Deng entropy. *Chaos, Solitons & Fractals* 2016, 91, 549–553. <https://doi.org/10.1016/j.chaos.2016.07.014>
- [19] Chen, Y.; et al. Measuring the uncertainty in the original and negation of evidence using belief entropy for conflict data fusion. *Entropy* 2021, 23, 402. <https://doi.org/10.3390/e23040402>
- [20] Xiao, F. Multi-sensor data fusion based on a generalised belief divergence measure. *arXiv preprint* 2018, arXiv:1806.01563. <https://doi.org/10.48550/arXiv.1806.01563>

- [21] Hamda, N.E.I.; et al. Multisensor data fusion in IoT environments in Dempster-Shafer theory setting: An improved evidence distance-based approach. *Sensors* 2023, 23, 5141. <https://doi.org/10.3390/s23115141>
- [22] Guo, Q.; et al. An evidence fusion method with importance discounting factors based on neutrosophic probability analysis in DSMT framework. *Neutrosophic Sets and Systems* 2021, 44, 129-141. <https://doi.org/10.5281/zenodo.1012213>
- [23] Sentz K, Ferson S. Combination of Evidence in Dempster-Shafer Theory. Contemporary pacific, 2002.<https://doi.org/10.2172/800792>.
- [24] Zhu, Jingwei; Wang, Xiaodan; Song, Yafei. Evaluating the Reliability Coefficient of a Sensor Based on the Training Data Within the Framework of Evidence Theory. *IEEE Access*, 2018, 6, 30592-30601, 2018. <https://doi.org/10.1109/ACCESS.2018.2816915>.
- [25] Guo, H.; et al. Evaluating sensor reliability in classification problems based on evidence theory. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* 2006 36, 970-981. <https://doi.org/10.1109/TSMCB.2006.872269>
- [26] Li, L.; Xu, G.; Wang, H. Supplier evaluation in green supply chain: An adaptive weight D-S theory model based on fuzzy-rough-sets-AHP method. *Journal of Information Processing Systems* 2019, 15, 1-15. <https://doi.org/10.3745/JIPS.04.0118>
- [27] Ma, W.; et al. A flexible rule for evidential combination in Dempster-Shafer theory of evidence. *Applied Soft Computing* 2019, 37, 5699-5708. <https://doi.org/10.1016/j.asoc.2019.105512>
- [28] Zhang, Z.; et al. A clustering coefficient structural entropy of complex networks. *Physica A: Statistical Mechanics and Its Applications* 2024, 650, 130170. <https://doi.org/10.1016/j.physa.2024.130170>
- [29] Zhou, Qianli; Cui, Ye; Pedrycz, Witold; Deng, Yong. Conjunctive and disjunctive combination rules in random permutation set theory: A layer-2 belief structure perspective. *Information Fusion*, 2024, 102. <https://doi.org/10.1016/j.inffus.2023.102083>.
- [30] Adolphs, P.; et al. Reference architecture model for Industry 4.0 (RAMI 4.0). *VDI/VDE Society for Measurement and Automatic Control* 2015. Available online: <https://www.din.de/blob/76902/e8cac883f42f28536e7d8167c3c0e4fe/rami-4-0-data.pdf> (accessed on 15 October 2024).
- [31] Tian, Z.; et al. Accurate and efficient parameter identification of fuel cells using tree seed algorithm based on adaptive differential evolution and Dempster-Shafer evidence theory. *Renewable Energy* 2026, 260, 125198. <https://doi.org/10.1016/j.renene.2026.125198>
- [32] Zhang, J.; et al. Quantifying potential cyber-attack risks in CNC systems under zero-subjectivity closed-loop Dempster-Shafer theory FMECA and rule-based Bayesian network modelling. *Reliability Engineering & System Safety* 2026, 274, 112427. <https://doi.org/10.1016/j.ress.2026.112427>
- [33] de Sousa, A.L.; de Oliveira, A.S. Deadlock-free production using Dempster-Shafer and preset methods in predictive scheduling for multiagent controlled flexible manufacturing systems. *Applied Soft Computing* 2024, 152, 111234. <https://doi.org/10.1016/j.asoc.2024.111234>
- [34] Liu, J.; et al. Sequential deterioration prediction of regional-scale building stock combining a two-phase regime-switching Markov model with the improved Dempster-Shafer evidence theory. *Reliability Engineering & System Safety* 2026, 269, 112105. <https://doi.org/10.1016/j.ress.2025.112105>
- [35] Dey, B.; Roy, B.; Mondal, N. Assessment of India's high ethanol blending future using a fuzzy-AHP and Dempster-Shafer-based decision model. In *Multi-Attribute Decision-Making: Theory, Emerging Methods, and Applications*; Springer: Cham, Switzerland, 2026; pp. 345-360.
- [36] Choutri, K.; et al. Enhanced fire detection: A weighted bounding box fusion approach based on Dempster-Shafer theory. *PeerJ Computer Science* 2026, 12, 3476. <https://doi.org/10.7717/peerj-cs.3476>
- [37] Alalaween W H , Alalawin A H , Gharaibeh B M ,et al.A Type-1 Fuzzy Fusion Model based on the Dempster-Shafer Theory for the simulation of 3D Fused Deposition. *Journal of Intelligent & Fuzzy Systems*, 2025, 49(5). <https://doi.org/10.1177/18758967251334236>.
- [38] Simeone, Alessandro; Grant, Rebecca; Ye, Weilin; Caggiano, Alessandra. A human-cyber-physical system for Operator 5.0 smart risk assessment. *International Journal of Advanced Manufacturing Technology*, 2023, 129, 5-6, 2763-2782. <https://doi.org/10.1007/s00170-023-12481-z>
- [39] Barrero-Arciniegas, Humberto Alejandro; Bataleblu, Ali Asghar; Rauch, Erwin; Matt, Dominik T. Sustainable and resilient cyber-physical production systems: A systematic literature review. *Journal of Computational Design and Engineering*, 2026, 13(5), 215-249. <https://doi.org/10.1093/jcde/qwag043>
- [40] Iram, Shamaila; Fernando, Terrence; Asim, Muhammad; Shakeel, Hafiz Muhammad. Intelligent framework of sustainable cyber-physical services for autonomous manufacturing industries. *Service Oriented Computing and Applications*, 2025, 19(4), 291-311. <https://doi.org/10.1007/s11761-024-00439-2>