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Federated Learning and Blockchain-Enabled Intelligent Manufacturing for Sustainable Energy Production in Industry 4.0

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Abstract: Intelligent manufacturing under Industry 4.0 assimilates sophisticated technologies and artificial intelligence for sustainable production and outcomes. Blockchain paradigms are coined with Industry 4.0 for concurrent and well-monitored flawless production. This article introduces Sustainable Production concerned with External Demands (SP-ED). This method is more specific about energy production and the distribution for flawless and outage-less supply. First, the energy demand is identified for internal and external users based on which sustainability is planned. Secondly, Ethereum blockchain monitoring for a similar production and demand satisfaction is coupled with the production system. From two perspectives, the monitoring and condition satisfaction processes are validated using federated learning (FL). The perspectives include demand distribution and production sustainability. In the demand distribution, the condition of meeting the actual requirement is validated. Contrarily, the flaws in internal and external supply due to production are identified in sustainability. The failing conditions in both perspectives are handled using blockchain records. The blockchain records reduce flaws in the new production by modifying the production plan according to the federated learning verifications. Therefore, the sustainability for internal and external demands is met through FL and blockchain integration.

Keywords: blockchain; federated learning; intelligent manufacturing; sustainable energy

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1. Introduction

Sustainability in various manufacturing aspects, such as energy, is achieved using intelligent processing in Industry 4.0. Sustainable energy comes from renewable sources such as wind power, water resources, and solar energy. Sustainable energy production is a crucial task to perform in industries [1]. Renewable energy applications and technologies are used in industries. Energy applications provide various services and policies to increase the sustainability range in energy production. An energy production scheme provides functions and services to perform specific tasks in industries [2]. Renewable energy production improves the energy-efficiency range of organizations. Sustainable energy production reduces the energy consumption ratio in Industry 4.0. Greenhouse gas (GHG) emission control is a complicated task to perform in industries. Greenhouse gas emission control uses various methods and techniques [3]. Artificial Intelligence (AI) technology is used in Industry 4.0—it increases the computational efficiency level of the systems. The AI method identifies the critical factors for the energy production process. The AI-based technique enhances industries' effectiveness and performance range [4]. Energy surplus or deficit may threaten the energy supply and demand security, leading to a demand–response issue in the industrial environment. It is becoming increasingly tricky to optimally schedule in a smart industry with varying energy consumption patterns and to engage in trustworthy energy trading due to potential privacy and security challenges in the distributed energy system.

Ethereum blockchain is the decentralized, open-source blockchain-based technology used for sustainable energy production in Industry 4.0. Blockchain-based techniques are mainly used in industries to detect problems and issues in the production process [5]. Blockchain techniques provide specific solutions to solve problems in production. For example, peer-to-peer transmission is carried out in manufacturing sectors, including effective assistance for sustainable energy production. Transmission and production contain various issues and threats that reduce the industry's production speed [6]. Essential qualities and attributes are identified in the database, yielding actionable data for multiple applications. The blockchain-based method identifies industries' potential benefits and features that provide necessary data for energy production [7]. A blockchain-based secure system is implemented in industries that increase the accuracy of sustainable energy production processes. The security system uses blockchain to initiate production based on certain conditions and functions. The Ethereum-blockchain-based data analysis method is also used in Industry 4.0, which analyzes the relevant datasets for the sustainable energy production process. The data analysis technique reduces the computation process' latency and energy consumption ratio [8,9]. Ethereum blockchain in industrial energy production allows for one to store the collected data (or proof of such data) to exchange them securely between entities that do not trust each other. Furthermore, blockchain technologies permit the creation of smart contracts, described as self-sufficient decentralized codes performed autonomously when certain conditions of an industry progression are met.

Machine learning (ML) models and techniques are widely used in various fields and applications. ML models are commonly used to improve production, computation efficiency, and feasibility range [10]. ML models are also used in Industry 4.0 for sustainable energy production. The convolutional neural network (CNN) algorithm is in the production model that performs specific industry tasks. CNN uses a feature extraction method that extracts the essential features and patterns from the database. CNN reduces the energy consumption range in computation, improving the efficiency ratio in the energy production process [11,12]. The support vector regression (SVR) technique is also used in sustainable production. SVR uses analysis that analyzes the data required for the production process. SVR increases the accuracy and performance range in Industry 4.0 [13,14]. The multiple linear regression (MLR) model is used for Industry 4.0, which implements a power forecasting system. The MLR model predicts the problems presented in the computation process, of which reduce the error range in sustainable energy production [15].

Sun et al. introduced a combined production scheduling model for sustainable manufacturing systems [16]. The primary goal of the presented model is to pinpoint the origin of the scheduling-related variation in resource use. The particle swarm optimization (PSO) algorithm is used here to analyze the data required for the scheduling process. PSO minimizes the overall time and energy consumption level in computation and scheduling processes. As a result, the proposed model enhances the performance and feasibility ratio of the manufacturing systems; however, the complex production efficiency modeling necessities need to be explored.

Li et al. introduced a digital twin-driven information mechanism for manufacturing systems [17]. A hierarchical analytic process analyzes the information relevant to scheduling and further processes. The digital twin mechanism uses evidence theory to build proper intelligent manufacturing techniques for the systems. The introduced method reduces the complexity and latency in the computation process. The presented strategy broadens the platforms' potential for efficiency and long-term sustainability. However, the incompleteness of primary data sources, the difficulty and uncertainty of actual indicators, and inaccuracy in human cognitive progression exist in the model procedure.

Majeed et al. developed an infrastructure for Sustainable and Smart Addiction Management (SSAM) using big data [18]. The proposed framework is mainly used for the decision-making process. Big data analytics identify the necessary data which are relevant for SSAM systems. The big data approach is mainly used for analyzing processes that reduce energy consumption in the identification process. The suggested architecture has been shown to improve the efficiency and functionality of SSAM systems in research conditions. However, due to the company's available capabilities and setup of IoT devices, the SSAM model can only be implemented in the first phases of a product's life cycle.

Psarommatis et al. presented a holistic approach to sustainable manufacturing systems [19]. Zero Defect Manufacturing (ZDM) is used here to improve the systems' efficiency and feasibility range. The suggested method's true motivation is to lessen the workload on the power grid during computing. ZDM is a required method since it supplies essential information and characteristics for production. In addition, the proposed approach increases the Quality of Service (QoS) in sustainable manufacturing systems. However, the suggested system data-driven model insufficiently attains the sustainable factor in the manufacturing process.

Ma et al. introduced a demand–response-based data-driven framework for a sustainable manufacturing system [20]. The goal of the proposed method is to manage multi-level requests which occur during the manufacturing process. The introduced framework reduces the computation cost and latency in manufacturing systems. The particle swarm optimization algorithm also manages the data required for various methods. The presented framework increases decision-making accuracy, enhancing the systems' performance. The suggested sustainable, innovative manufacturing model only considers the product lifecycle's manufacturing phase, disregarding other stages, such as operation, design, recycling, maintenance, and remanufacturing.

Tian et al. introduced dynamic evaluation based on correlation relationships for sustainable manufacturing in industrial cloud robots (ICR) [21]. Correlation relationships produce appropriate data which are related to assessments. The suggested technique may identify issues throughout the computation and provide a workable answer to fix them. The proposed approach has a lower energy usage ratio in the calculation compared to prior methods. The recommended strategy increases ICR's efficiency and dependability. Impacting sustainability objectives must be considered when developing a more comprehensive evaluation indicator.

Jasiulewicz-Kaczmarek et al. introduced a multiple-criteria approach for manufacturing systems [22]. The method offered is a continuous sustainability performance evaluation based on fuzzy set theory. The presented method uses a maintenance indicator that identifies the synthetic index and patterns necessary for the assessment process. The maintenance indicator reduces the time consumption ratio in both computation and identification processes. The introduced approach improves the manufacturing systems' overall sustainability and feasibility range. However, several aggregation functions have a limitation, primarily from their natural assumption that input criteria are independent.

Zimmermann et al. designed an action-oriented teaching approach for an intelligent precision manufacturing system [23]. The proposed method detects the exact demands and reasons for requests in manufacturing systems. Various machine tools are also used in a teaching approach that provides certain services in the decision-making process. An intelligent-based reduction strategy is used here that reduces the latency rate in assessment and scheduling processes. The systems' effectiveness and energy efficiency are improved by the proposed method. However, the limitation concerning the included thermal errors and the inadequate prediction accuracy makes an extensive industrial application unrealistic.

Wang et al. developed an energy consumption intelligent model for additive manufacturing (AM) systems [24]. A multisource fusion method is used in the proposed model that identifies the exact data from the database. The proposed model is mainly used for 3D printing (3DP), which detects the necessary pixels and features from the images. As the experiments show, the suggested model improves the AM devices' efficiency range. However, modeling energy consumption and forecasting with multiple source data are infrequent. The residues obscure how various sources can be leveraged to effectively learn a detailed depiction of the prediction task.

Favi et al. proposed an energy management framework for a sustainable life cycle in Industry 4.0 [25]. The proposed structural framework uses energy material flow analysis

(EMFA) for the data analysis. Key Performance Indicators (KPIs) are used in industries that identify the exact production performance ratio of the systems. KPI provides relevant data for decision-making and allocation processes. The proposed framework minimizes the material flow range in industries. Furthermore, the efficiency in supporting companies in the analysis, managing production plants' energy, and identifying criticalities and material flows have yet to be verified.

Pei et al. introduced an approximation algorithm for unrelated parallel machine scheduling in manufacturing systems [26]. The suggested method aims to reduce manufacturing systems' electric power consumption rate. The introduced algorithm identifies the regional problems that occurred during the manufacturing process. The proposed approach improves the precision of machine scheduling, which strengthens the systems overall. The new algorithm enhances both the speed and accuracy of existing systems. However, one commonly known disadvantage of the branch and bound technique is its time-consuming feature.

Cañas et al. designed a conceptual framework for Smart Production Planning and Control (SPPC) in Industry 4.0 [27]. Small- and medium-sized (SMEs) businesses are the primary users of the proposed framework. The proposed framework provides a systematic structure to analyze the relevant data for the SPPC process. As a result, the conceptual framework enhances the efficiency and accuracy of SPPC4.0. Furthermore, compared with other frameworks, the proposed framework achieves high performance in scheduling processes. However, it must be noted that multidisciplinary engineering is essential for establishing SPPC 4.0 models.

Friederich et al. introduced a standardized data-driven architecture for intelligent production systems [28]. The proposed framework aims to maintain the data in digital-twin-based systems. Machine learning (ML) and data mining techniques are used here to reduce the computation process' complexity. ML techniques are mainly used here for the validation and detection process. The introduced framework enhances the effectiveness and feasibility range of smart manufacturing systems. However, due to issues with devices, networks, etc., data may be incomplete.

Gu et al. developed a cyber–physical architecture for smart factories [29]. The architecture implements a deep reinforcement learning (DRL) algorithm that detects the relevant data for different processes. DRL selects the necessary information for decision-making, reducing the computation process' latency and energy consumption. The suggested strategy also improves the systems' effectiveness by boosting the precision of their decision-making and planning. However, a single scheduling rule cannot preserve high-quality scheduling efficiency in the face of orders of dissimilar sizes.

Liu et al. proposed product lifecycle management (PLM) infrastructure for Industry 4.0 based on blockchain technology [30]. The blockchain technique identifies the exact relationship among the nodes that provide optimal data for the scheduling process. Blockchain also detects the problems which occur during manufacturing. The conceptual approach reduces PLM systems' overall time-to-energy ratio. The proposed platform increases PLM's long-term viability and scope of industrial importance. This study still needs to implement the real-life case-study use fully; thus, existing outcomes supported the possibility of implementing this platform but cannot make a quantitative comparison with conventional PLM platforms.

Krithika L. B. [31] discussed the advancements in blockchain technology that have shown promising properties that might be useful in farming. There have been some helpful upheavals and progressive acceptance of blockchain in agribusiness owing to the development and rollout of blockchain, which has helped to modernize the sector. Decent quality development in farming has led to the use of blockchain technology at several stages of the process. This research comprehensively examines the existing research on the opportunities and threats posed by blockchain technology in the agricultural sector. Much of the study is in its infancy, the PoCs are based on outdated versions of blockchain, and the concept has undergone significant rehabilitation since its beginnings.

Guruprakash Jayabalasamy and Srinivas Koppu [32] suggested nonrepudiation in Internet of Things (IoT) apps developed on blockchain using High-Performance Edwards Curve Aggregate Signatures (HECAS). Compared to the standard digital signature model, the signing and verifying procedures created in the present study took 10% and 13% less time to process, respectively. Additionally, using HECAS in a blockchain context may reduce storage costs by 40%, improve transaction flows by 10%, and improve block validation by 10% compared to a system that does not use HECAS. Finally, the author tested their technology by simulating several blockchain-based Internet of Things systems. As a result of their efforts, blockchain-based technologies for the smart Internet of Things may produce effective, consistent results across various sensor types.

The leakage or collision of secret keys is possible if two identities are generated using the same randomized integer.

Zixiao Xu et al. [33] suggested a blockchain-based power trading and bidding mechanism for several microgrids. Consequently, to accomplish source–sale integration, a competitive spot market with scattered "multi-seller and multi-buyer" was constructed. Researchers in this study compared and contrasted traditional power trading with a blockchain-based alternative. In addition, an ant colony optimization technique was used for randomized bidding matching, and a blockchain-based multi-microgrid energy trading model was developed. This method integrates the transfer of energy, data, and money into a single procedure. Lastly, the efficient allocation of power resources was ensured by openness and transparency in power transactions. Nonetheless, business still needs to develop and improve the Energy Internet trading system.

Qu et al. [34] introduced federated learning and a blockchain-based distributed approach for Data-Driven Cognitive Computing (D2C). Federated learning's emphasis on privacy and efficiency makes it well-suited to address the "data island" issue. In contrast, blockchain's reward mechanism, completely decentralized nature, and resistance to poisoning assaults make it an attractive complement. Improvements in decision-making and data-driven intelligent manufacturing are already visible thanks to the development of different AI and machine learning technologies. Furthermore, rapid convergence may be achieved via sophisticated verifications and member choices made possible by blockchain-enabled federated learning. The results of a comprehensive review and assessment show that D2C is superior to the state-of-the-art in terms of efficiency.

Zhao et al. [35] proposed a federated learning (FL) system that uses a reputation mechanism to allow for home appliance makers to train a machine learning model using data from actual consumers to facilitate the development of an intelligent home system. The first step in the system's workflow involves users training the manufacturer-supplied baseline model on their mobile device and the mobile edge computing (MEC) server in addition to an incentive system to reward participants for enticing more consumers to participate in the crowd-sourced FL work.

Energy surplus or deficit may threaten the energy supply and demand security, leading to a demand–response issue in the industrial environment. It is becoming increasingly more work to optimally schedule in an intelligent industry with varying energy consumption patterns and to engage in trustworthy energy trading due to potential privacy and security challenges in the distributed energy system. Based on the survey, there are several challenges in existing methods in achieving high sustainability factors, attack detection time, modifications, and flaw detection for energy supply–demand. Hence, in this paper, Sustainable Production concerned with External Demands (SP-ED) has been proposed for practical energy production and distribution for flawless and outage-less supply.

2. Sustainable Production Concerned with External Demands

The features of Ethereum blockchain are used in Industry 4.0 for a synchronous and well-observed, flawless production. This method introduces Sustainable Production concerned with External Demands [SP-ED]. This method is used for energy production and the distribution of flawless outages. Industry 4.0 evolves many technologies, and blockchain is one of them. Blockchain enhances the Industry 4.0's security, privacy, and data transparency. This Industry 4.0 enables the manufacturers to achieve their goals in a more agile and quick way. Blockchain is used to attain more identification and improve the manufacturing environment. As blockchain is more straightforward and less intermediary, it is used to defend their inventions. Using this blockchain technology in Industry 4.0 enhances their competitiveness, which can access the world of copyrights. This unique technology eliminates transaction communication, effectively as a productive production flow. Decentralized energy trade and supply, the safe records of all industrial activities in energy generation, and the effective automated management of energy and storage flow via smart contracts are ways the Ethereum blockchain with FL might benefit the energy sector. This proposed SP-ED is portrayed in Figure 1.

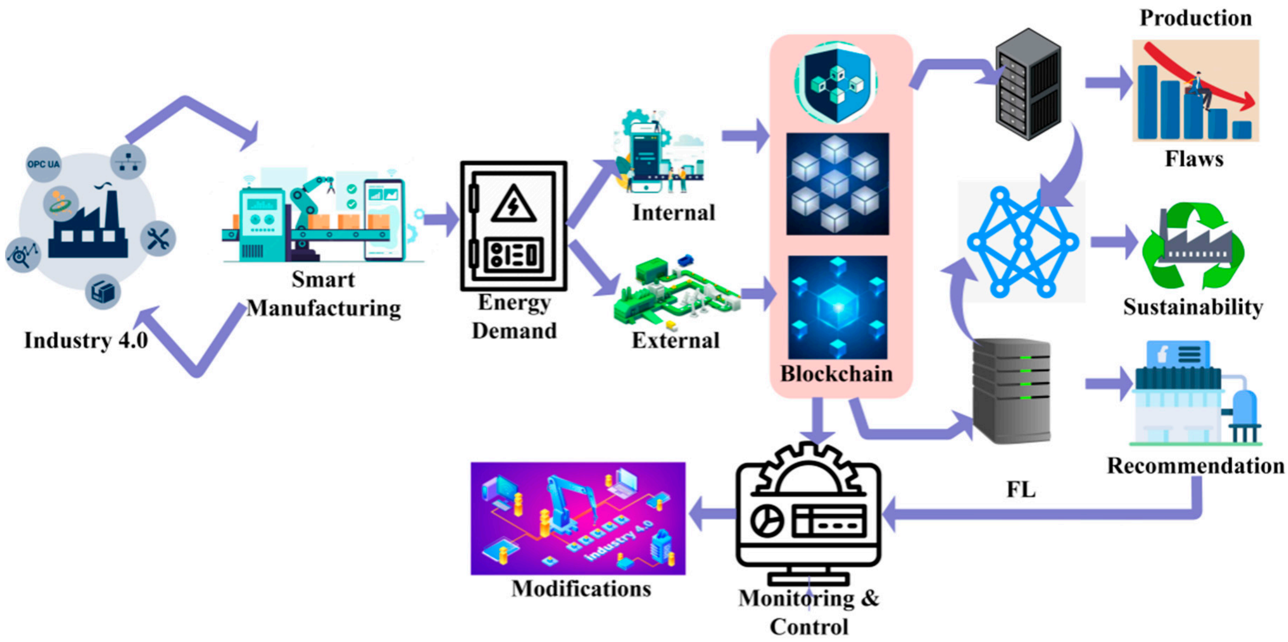

Figure 1. SP-ED illustration.

This method's manufacturing process is the modern version of automation. The manufacturing process depends on the energy demand to improve energy sustainability during the production of goods. The internal and external demands are identified from the energy demand. Internal demand is the one that has the energy used in the process of manufacturing. External demand is the one that contains the excess energy not used in the procedure of manufacturing. Blockchain technology observes these internal and external demands, which will be given as input to federated learning (FL). This FL checks the demands, distribution of energy, and energy consumption. From this FL, the production flaws, energy sustainability, and recommendations are obtained. These production flaws check the energy distribution and the internal usage of energy. If the energy is insufficient, it can be identified in this process. Energy sustainability checks how long the energy lasts to achieve the demand. A recommendation is used to recommend scheduling the energy and time depending on the output. From the blockchain, the monitor control takes place. Based on the input in the blockchain, the modification process is carried out to improve the manufacturing procedure. Ethereum blockchain technology can improve energy efficiency and give consumers more control over their utilities in the industrial environment.

Furthermore, the data on how much energy is used is updated securely and promptly due to an immutable ledger. Here, the intelligent manufacturing process is carried out in Industry 4.0 based on the energy demand. X_1, X_2 are the subset of variance to calculate the energy consumption. The process of enhancing the manufacturing procedure by the energy demand is explained by Equation (1), as given below:

$$a - b - c(X_1 + X_2),\ if\ 0 \leq X_1 + X_2 \leq b/c - 0, \quad (1)$$

where a is denoted as the measure of observation, b represents the data feature, c is the covariance of data, and X_1 and X_2 are characterized as the internal and external energy demand. Now, from the energy demand, the sustainability of the energy can be improved. Then, the internal demand and the external demand are identified. In this internal demand, the information on the energy used in the manufacturing process can be determined. This is used to obtain information on the energy that can enhance manufacturing in Industry 4.0. This also determines the energy utilized in the process and how much energy can be saved. Based on the demand, the energy can be accommodated for internal usage, and thus it will be helpful in flawless production. The internal demand accumulates the amount of energy that is needed in the manufacturing process. Additionally, it does not occupy unnecessary energy consumption, which will not be used during the process. This information can be observed by blockchain technology later, and it gives input for the upcoming process. Thus, the internal demand stores the needed energy during the manufacturing process. This eliminates the excess energy which is not required for the process. This procedure is used to enhance energy sustainability to produce flawless execution. The internal demand is extracted from the energy demand to improve manufacturing. This also helps identify the needed amount of energy for the process and helps make the energy last longer during flawless production. This process of internal demand usage is based on the sustainability plan. Equation (2) below explains the process of extracting the internal demand and its functions. d_1 and d_2 are the internal demand parameters, and the energy function is denoted as C.

$$\left.\begin{array}{l} \pi_1 - \pi_1(\gamma_1, \gamma_2) - (b - CX_1 - CX_2 - d_1)X_1 \\ \pi_2 - \pi_2(\gamma_1, \gamma_2) - (b - CX_1 - CX_2 - d_2)X_2 \end{array}\right\} \quad (2)$$

where (π_1, π_2) is denoted as the mean of all observations and (γ) is represented as the energy variance during the manufacturing process. Now, the external demand is extracted from the energy demand. In this external demand, the excess energy not used for the process is stored. Based on the energy demand, the amount of energy can be used for the process. Then, if an excessive amount of energy is occupied, it will be stored in the external demand. This extreme energy can be used for the upcoming process in production. This can be well monitored by blockchain technology and given as the input for federated learning. Based on the energy demand, the energy can be used for manufacturing. The energy utilized in the process is stored in the internal demand, and the energy not utilized will be stored in the external demand. Thus, the excessive amount of unused energy will be helpful in the other flawless production process. This will be helpful to the observation process, which is carried out by blockchain technology. Internal and external demands are based on the energy demand for the manufacturing process. The external demand is used to accumulate the excess energy which is not used in the manufacturing process. This excessive energy acquired during the process can be helpful in the upcoming flawless production process. Both internal and external energy is used to improve energy sustainability. This sustainable energy will last longer in the manufacturing process and production processes. Equation (3) below explains the process of obtaining the external demand from the energy demand for manufacturing.

$$\left.\begin{array}{c} L_1 - L_2(X_1, X_2) - \gamma_1\pi_1 + (1 - \gamma_1)Q_1 - (b - CX_1 - CX_2 - d_1)X_1, [\gamma_1 - 1] \\ M_1 - M_2(X_1, X_2) - \gamma_2\pi_2 + (1 - \gamma_2)Q_2 - (b - CX_1 - CX_2)X_2 - \gamma_2 d_2 X_2, [\{\gamma_2/\gamma_2 \leq 1\}] \end{array}\right\} \quad (3)$$

where (L_1, L_2) is denoted as the different energy demand levels and M_1 and M_2 are denoted as the excessive energy monitored in manufacturing and production levels. Now, the internal demand and the external demand are observed by blockchain technology. This observed information value is given as the input to the federated learning. Furthermore, this blockchain process can identify the energy used and available for the upcoming process. The blockchain implication for internal and external monitoring is illustrated in Figure 2.

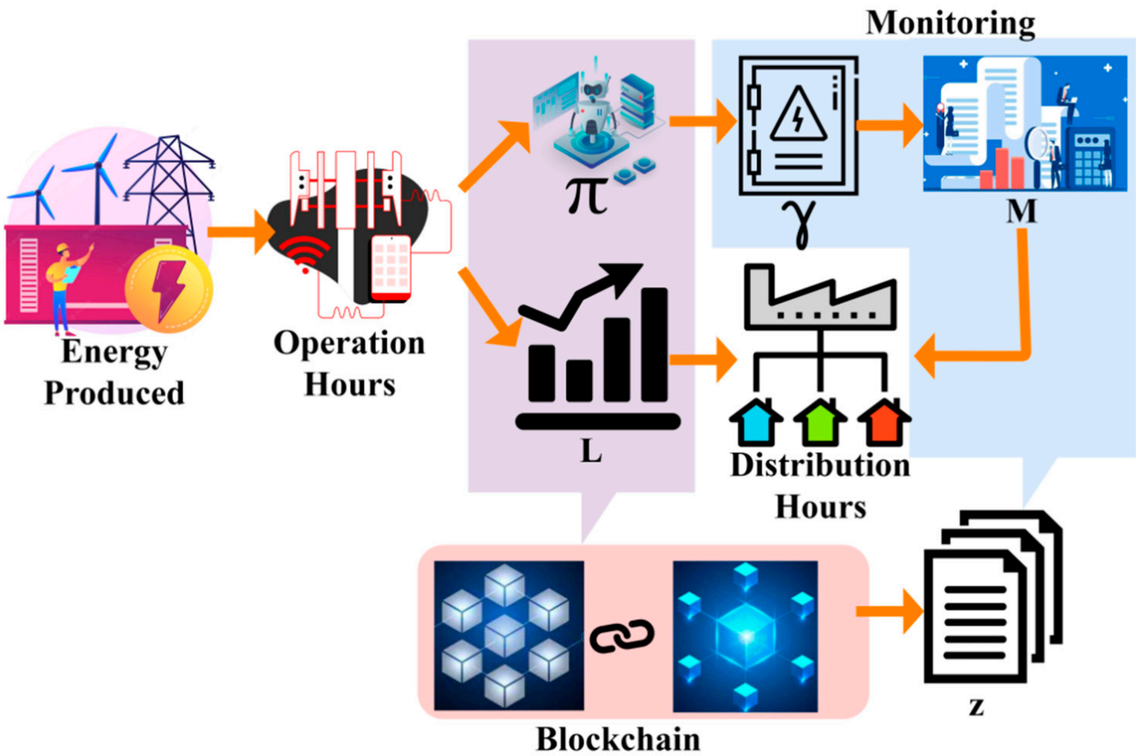

Figure 2. Blockchain implication.

Ethereum blockchain monitoring is used for similar products, and demand satisfaction is carried out in the production system. This process is used to check whether it satisfies the production system and whether it carries out the demanded process. This blockchain technology will obtain the energy used to fit the demand. It took care of both the demand and production satisfaction coextending. If there is any issue in the process, blockchain technology takes a further step to resolve the problems. It is used to check whether the demand satisfaction is met and the production flow. It also assumes energy and excessive energy consumption in the internal and external demand (Figure 2). Based on this input, federated learning is used for flawless production. In this technology, more identification is attained to produce the perfect deliverance without any flaws.

Ethereum blockchain technology is used to manage energy, which satisfies both the production and the demand. It is also used to observe the entire internal and external demand process extracted from the energy demand. It can be given as input to FL for production without flaws. It can also help monitor the control process. It has information about the used and unused energy for manufacturing and production. Therefore, it can be observed by satisfying both the presentation and demand during flawless execution. This process of observing blockchain technology's internal and external demand is explained by Equation (4) below:

$$\left.\begin{array}{c} \alpha(X_2) - X_1 b - \frac{d_1}{2a} - \frac{X_2}{2} \\ \beta(X_1, X_2) - X_2 - \frac{b - \gamma_2 d_2}{2a} - \frac{X_2}{2} \\ \alpha(\gamma_2) - \frac{b - 2d_1 + \gamma_2 d_2}{2b} \\ \beta(\gamma_2) - \frac{b - 2\gamma_2 d_2 + d_1}{2b} \end{array}\right\} \quad (4)$$

where α denotes the performance threshold of the blockchain technology, β is the energy evaluation function, γ is represented as the output of the internal and external demand from the energy demand, and d is the energy distribution. The observed information by the blockchain technology is sent as input to federated learning. The FL validates the monitoring and condition satisfaction processes from two perspectives. This perspective includes the distribution of the demand and the sustainability of the production. In the distribution of the demand perspective, the condition is validated to meet the actual requirement. FL is used for the intelligent manufacturing process by using sustainable energy. It uses the input given by the blockchain for flawless production. It is used to check the sustainability of production and demand distribution. It also verifies whether the energy can satisfy the demand and execute a perfect show. It also has information about the energy consumption and distribution rate used to fulfill the need. It is used to enhance energy sustainability during manufacturing and production processes. It is also used to validate whether the condition meets the actual requirement. The input given by the blockchain to FL is used in the monitoring control for further modification. Then, it is also used in FL for the perfect flawless production with good energy sustainability. The FL functions are explained in Figure 3.

Figure 3. FL functions.

Federated learning is an ML method that trains an algorithm across servers holding local data samples and multiple decentralized edge devices. FL allows for ML to be used locally without transmitting data to a centralized server. The centralized storage permits the evaluation progression to work fully asynchronously. Since every FL training round creates a model for every user and a united model resulting from the merge procedure, the number of models grows fast. The blockchain and federated-learning-assisted solution deliver secure energy distribution between industrial applications. Federated learning is used to verify the demand distribution and the sustainability of the production with the two perspectives. The input given by the Ethereum blockchain to FL checks whether it satisfies the actual requirement and checks the availability and sustainability of the energy to meet the demand. The FL extracts the production flaws, energy sustainability, and recommendation. It can validate the energy state for the manufacturing process and flawless production (Figure 3). The distribution rate and energy consumption can be identified through FL. The method of FL using the input given by blockchain technology is explained by Equations (5) and (6), as given below:

$$\left.\begin{array}{r}\forall_1(\gamma_2) - \frac{b-(2d_1+\gamma_2 d_2)^2}{Z} \\ \forall_2(\gamma_2) - \frac{(b-d_2+d_1+\gamma_2 d_2)(b-\gamma_2 d_2+d_1)^2}{Z}\end{array}\right\} \tag{5}$$

$$\sum_{z}^{*} = \frac{d_2 - b_1 - a}{d_2} \tag{6}$$

where $(\forall)$ is denoted as the normalization vector of federated learning, $(\sum_{z}^{*})$ is designated as the energy distribution rate, and Z represents the production flaws. Now, the production flaws, energy sustainability, and recommendation are extracted from FL. The production flaws verify the internal usage of energy. Additionally, they also check whether there needs to be more energy to lead the manufacturing process. Suppose there is an issue in the distribution process due to insufficient energy—in this case, the needed energy is given, and the redistribution process is carried out to the flawless production. It is used to check whether it satisfies the energy demand and sustainability. If there are any flaws during the show, further steps are taken to resolve the insufficient energy. After verifying the internal usage of energy, the needed amount is calculated for the other process. The redistribution process eliminates the flaws and makes the energy so long for the production process. The redistribution is made to improve the manufacturing process in the industry without any time delays and defects. It can also be used in the improvement in demand and product satisfaction. More energy can be identified, and further steps are taken to enhance the sustainability of energy. The production flaws were used to check whether the production rate met the demand satisfaction without flaws and insufficient energy. FL verifies production distribution and demand satisfaction, and the production flaws are obtained from that. If there is an inadequate amount of energy in the process, then the redistribution process is carried out with sufficient energy needed for the perfect manufacturing process. The method of production flaws obtained from FL is explained by Equation (7) below:

$$((\gamma_1^*, \gamma_2^*), (X_1(\beta_1, \beta_2), X_2(\gamma_1, \gamma_2)) - \left(\left(1, \frac{bd_2 - d_1 - b}{d_2}\right), \left(\frac{b - 2d_1 + \gamma_2 d_2}{b}, \frac{b - 2\gamma_2 c_2 + d_1}{b}\right)\right) \tag{7}$$

where (γ_1^*) is denoted as the rate of production flaws during manufacturing. Now, the energy sustainability is verified by FL. Here, it demonstrates how long the energy lasts to achieve the demands. Additionally, internal and external energy supply flaws during production are identified. They are used to verify the sustainability of the energy from the energy demand. The Ethereum blockchain makes the input for FL; thus, the flaws and production rate can be determined. These are the things that have information about the energy used in manufacturing. If there is excessive energy in the external demand, it will be used for the redistribution process when there is insufficient energy. The FL is used to enhance the sustainability of the energy in order to last a long time to meet the demand satisfaction. It also improves the production process without any flaws in it.

Energy sustainability checks whether energy can last far for the required demand and improves the production rate. The condition of meeting the requirement is also validated in this energy sustainability. From the input of the Ethereum blockchain, these features are extracted and used to improve the production rate and the manufacturing process in Industry 4.0. The sustainability of the energy helps in the elimination of flaws and increases the production rate. The energy sustainability process validates the appropriate value of energy consumption. It also makes the process effective and improves the satisfaction of the required demands during manufacturing. The method of energy sustainability verification from FL by the input of the blockchain is explained by Equation (8), as given below.

$$\left.\begin{array}{l} X_1^*(\gamma) = \frac{b-Vd_1+d_2}{\eta} \\ X_2^*(P) = \frac{b-Vd_2+d_1}{\eta} \end{array}\right\} \quad (8)$$

where (X_1^*) is denoted as the sustainability of the energy, η is designated as the process carried out by the sustainable energy production, and V is the volume of the energy characterized as the output of FL. Now, the recommendation takes place from the FL processes. This recommendation gives information about sufficient and insufficient energy, scheduling the time and energy. By this, other methods can be carried out for the manufacturing process. It provides recommendations to alter the current approach to meet the demand after flawless production. This information makes changes for the successful production process without flaws and delays. The recommendation information is preferred for the following methods by changing accordingly with the perfect amount of energy and time. The recommendation flow based on decisions is presented in Figure 4.

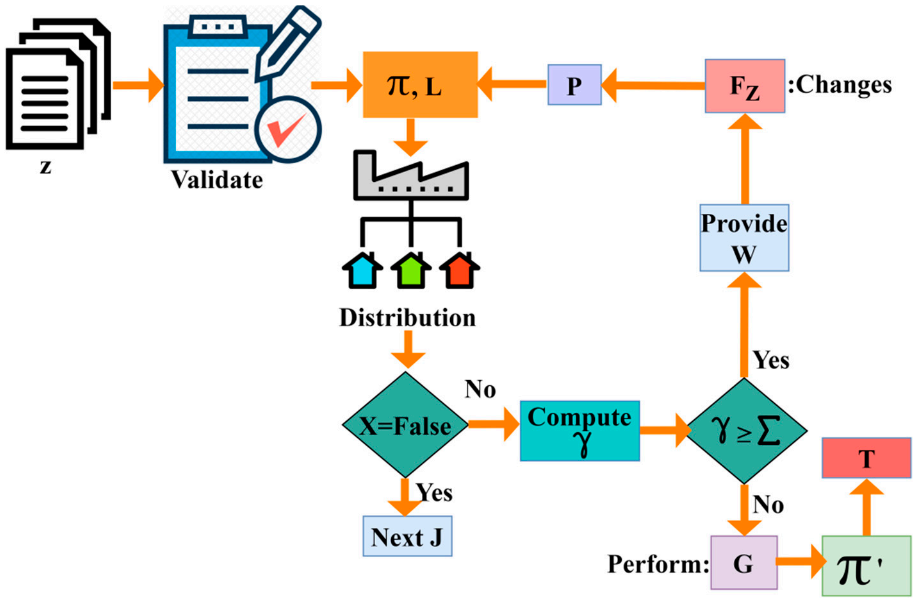

Figure 4. Recommendation flow.

The recommendation includes what to change and add for the upcoming processes. With this reference, the changes are made for the speedy manufacturing process in Industry 4.0. These changes can be stored in the blockchain records for further modification processes. In addition, it is given as input for the monitoring control process in the industry (refer to Figure 4). The recommendation process extracted from FL with the blockchain input is explained by Equation (9), as given below:

$$W(X_1, \gamma_2) - \frac{b - GX_1 - \gamma_2 d_2}{a} \quad (9)$$

where (W) is denoted as the weighted recommendation for the process and (G) is designated as the energy gain. Now, the monitoring control process takes place from the blockchain records. The observed information by the Ethereum blockchain modification is carried out accordingly. By monitoring the production plan based on the federated learning verification, the Ethereum blockchain records can be used to reduce the flaws in production. The monitoring control process is explained by Equations (10) and (11), as given below:

$$\pi_1' - \pi_1'(X_1\gamma_2) - \left(\frac{b - GX_1 - \gamma_2 d_2 - 2J_1}{a}\right)X_1 \quad (10)$$

$$\pi_2' - \pi_2^1(X_1\gamma_2) - \frac{(b - GX_1 + \gamma_2 d_2 - 2J_2)(b - CX_1 - \gamma_2 d_2)}{2a} \quad (11)$$

where (π_1') is denoted as the monitoring control process and (J) is represented as the flaw rate obtained during production. The modification is carried out for the new production process based on the monitoring control output. Improvement is made to improve the sustainability and production rate during manufacturing. The changes are made according to the records in the Ethereum blockchain and the validation of FL. These can help produce a productive manufacturing process in Industry 4.0. The method of the modification procedure carried out based on the Ethereum blockchain records and FL validation is explained by Equations (12) and (13), as given below:

$$\sum_{z}^{*} X_1(\gamma_2) - \frac{b + T_2 d_2 - 2d_1}{2a} \quad (12)$$

$$F_z(X_1) - 1 \quad (13)$$

where (F_z) is denoted as the functionality changes made to improve the manufacturing process and (T) is the required time in the manufacturing due to the Ethereum blockchain. Hence, this method uses Ethereum blockchain technology and federated learning to improve the production rate and manufacturing process. The sustainability for internal and external demand from the energy demand is met through FL and blockchain support integration. Here, the processing time is reduced and the flaw ratio is decreased. As a result, the sustainability of the energy is high during the manufacturing process. This method helps in the improvement in production and demand satisfaction. From the considered dataset, the monitoring control process is illustrated. The monitoring control process is shown in Figure 5.

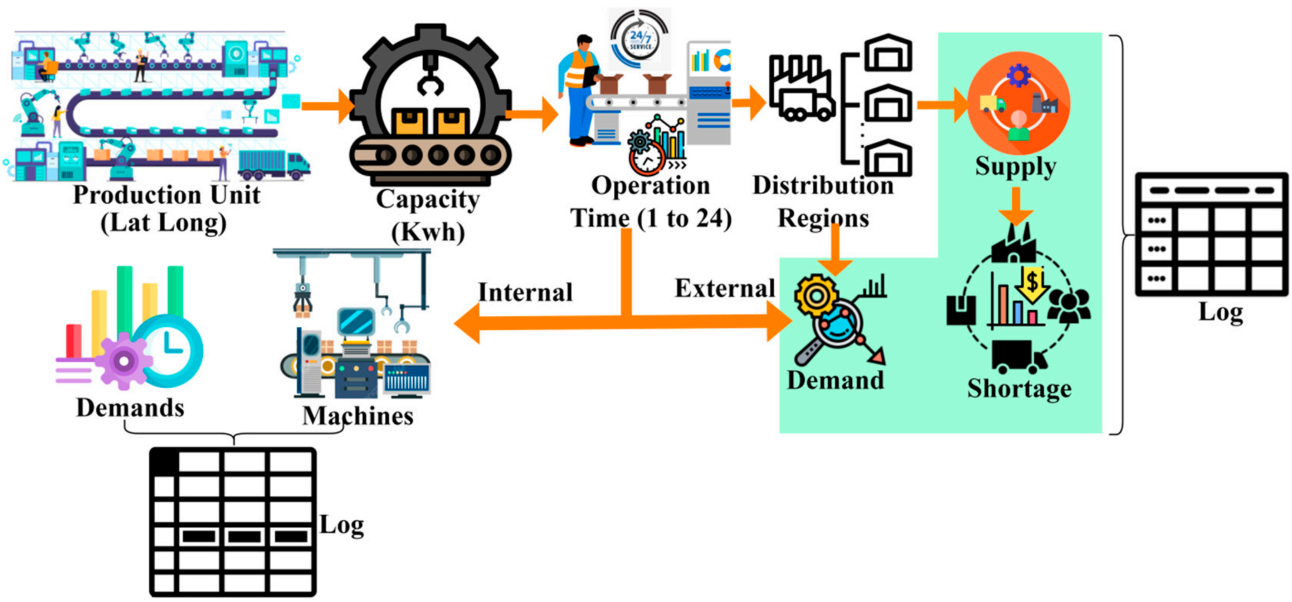

Figure 5. Monitoring control process using the considered data.

The production unit (industry) is located by its latitude (Lat) and longitude (long) markers. Based on the capacity, the distribution regions are organized. The generated energy is split into internal (machines) and external (public) distributions. The log post the single operation cycle provides the next cycle's shortage, consumption, and requirements. The T is predominantly performed for internal and external distributions (Figure 5).

3. Dataset Description

The dataset from [36] is used for validating the SP-ED and verifies sustainability. Data on greenhouse gas emissions supplied by significant emitters to the United States Environmental Protection Agency's (EPA) Greenhouse Gas Reporting Program (GHGRP) are used to calculate energy usage from commercial combustion at the plant level. Information on fuel usage is calculated using the EPA's standard pollutants factors. The values for the amount of energy required to burn fuel at a specific facility are calculated based on several factors, including sector (six-digit NAICS code), geographic coordinates (elevation, meridian, zip/postal code, county, and state), type of combustor, and name of the unit. The manufacturer's North American Industrial Classification System (NAICS) codes may further define combustion energy consumption by identifying energy end-use (e.g., conventional boiler use, co-generation/CHP utilization, process heating, and other facility support). The proportion of combustion fuel energy utilized for each end-use group in assembly plants may be calculated using data from the 2010 Manufacturing Energy Consumption Survey (MECS, produced by the Energy Information Administration), using the NAICS code and the stated fuel type. Based on industrial combustion energy, two observations are presented. The first observation is the attributes such as location, operation time, etc., as illustrated in Figure 5. The second observation is the utilization and sustainability of energy generation and distribution. In the first observation, a total of 20,118 (with average production) and 183 entries are jointly used for assessment in the second observation. The joint evaluation is performed according to 20 cycles for internal and external distribution. The number of nodes included in the eight industrial nodes and the amount of data available to each node in federated learning is two. The two blockchain networks were evaluated as potential components of the experimental setup's distributed ecosystem. Each benchmark included 1000 transactions sent at speeds ranging from 20 to 500 transactions per second to determine the maximum, average, and lowest transaction latency and throughput. Sustainability is accounted as the maximum possible distribution ratio that is consistently achieved in maximum operation cycles. Based on π and L, the actual representation in the dataset for sustainability is presented in Table 1.

Table 1. π & L representation from the data set.

Cycles	π (kWh)	Distribution (kWh)	M_1	L (kWh)	Distribution (kWh)	M_2
2	65.23	64.36	0.87	133.79	133.79	0
4	61.2	61.2	0	259.32	251.36	7.96
6	82.36	78.35	4.1	458.23	452.36	5.87
8	231.21	213.16	18.05	369.6	362.31	7.29
10	198.36	190.3	8.06	698.25	690.58	7.67
12	254.36	251.36	3.0	784.62	785.3	−0.68
14	274.63	269.54	5.90	1008.1	1008.1	0
16	289.46	285.34	4.12	985.36	878.36	107.0
18	303.05	301.21	1.84	874.23	870.69	3.54
20	298.25	298.25	0	963.21	962.21	1.0

The π and L different cycles are tabulated above, wherein π shows up more minor variations. Contrarily, L is different due to the distribution regions and unpredictable consumptions. In the π distribution, the fixed count of machines serves the purpose of planning the distribution beforehand. Therefore, the maximum utilization is improved, from which an excess is reported if the machinery is not functional. In this case, M_1 (extreme) is augmented for $L-$based distribution. However, M_2, a cycle modification, is comparatively high and therefore is required to prevent flaws. Pursued by the above represents the data recorded by the blockchain for identifying defects. For example, if the M_2 is vast even after M_1 scheduling, then the production needs to be modified. Therefore, the revisiting cycle across the different working machines is pursued under modifications. It is represented in Figure 6.

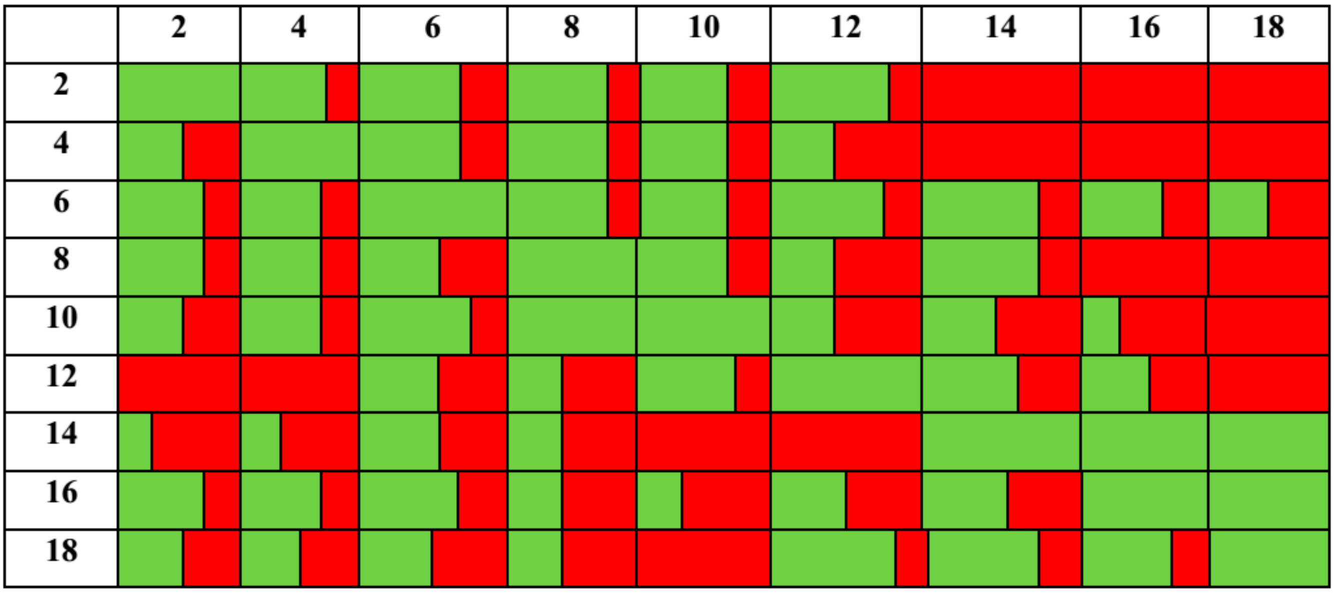

Figure 6. Revisited cycle for different hours.

The representation in Figure 6 presents four different combinations—namely, excessive (green), semi-demand (half red-half green), demand (red), and depleting (red concentration is high). Therefore, the depleting- and demand-based combinations are revisited to prevent distribution flaws. Based on (α, β) all depletion and demand, (α, β) is analyzed between successive cycles. In this process, γ^* due to a lack occurs, and hence, F_z is required. This represents the precise cycle for which modification is required. A total of 141 changes (internal 16, external 125) are observed in a given dataset. As the internal is significantly less, we discard it; the sustainability for 125 is analyzed in Table 2.

Table 2. (V, η) for 120 modifications.

Modifications	Flaw Detection (%)	X^*	Excessive Distribution (kWh)	(V,η)	Revisiting Required
20	13.06	0.365	98.56	0.658	1
40	21.36	0.263	137.604	0.462	3
60	25.69	0.458	121.36	0.541	2
80	29.69	0.547	69.25	0.745	2
100	32.45	0.619	12.39	0.883	0
120	36.46	0.587	58.25	0.851	1

The actual modifications are required to prevent frequent F_Z between the operating cycles. Therefore, sustainability is short-lived, and thus the new $\gamma*$ is identified. The $(M_1 + M_2) \forall (L)$ distribution is planned using G, such that π^* induces successful allocation.

This is further studied using the blockchain output for the logs (α, β). In this process, W is the modification, and T for preventing sustainability falls (Table 2). Following this process, the flaw minimization duet to M and G is analyzed in Table 3 data.

Table 3. Flaws for varying $G = 1\ to\ 7$.

G	W	(V,η)	Distribution	Flaws (/Cycle)
1	3	0.883	0.955	6
2	5	0.584	0.854	4
3	4	0.651	0.654	5
4	12	0.521	0.741	3
5	18	0.591	0.845	1
6	16	0.625	0.745	2
7	27	0.462	0.608	0

The flaw minimization is achieved by increasing the distribution and sustainability. W is segregated from multiple intervals (cycles) to improve the distribution. This is achieved by considering (α, β) various d_1, d_2 and γ of the FL process. Any flaws are tracked and addressed by providing precise G between T's, and hence, appropriate demands are satisfied. This generates no hassle in further distribution, thus preventing defects (Table 3).

4. Comparative Discussion

The comparative analysis uses the metrics sustainability factor, flaw detection, demand satisfaction, modifications, and detection time. The operating hours and supply-to-demand factors are modified accordingly. Alongside the proposed method, the existing MQIP-TOU [26], DDSIM [20], and GDDF [28] methods are considered. However, several current ways have limitations, such as complex production efficiency, a high time-consuming feature, and inadequate prediction accurateness. When compared to all of the existing methods, the proposed method has higher efficiency, which is discussed as follows:

4.1. Sustainability Factor

The efficacy of the sustainability factor is high in this method by using Ethereum blockchain technology and the federated learning technique. Based on the energy demand, the manufacturing process is carried out. From the energy demand, the internal and external demand is extracted. By using this demand, the use and the excessive amount of energy can be determined. Energy demand is used to enhance the sustainability of the energy during flawless production. Blockchain technology is used to observe the internal and external needs and provides input to FL. Monitoring control is also carried out based on blockchain records and FL validation. From this, modifications are made to improve the redistribution and satisfaction of production. This process helps to strengthen both demand and production satisfaction. Using Equation (5), the sustainability factor has been determined for the energy production system. By improving energy sustainability, the flaws can be reduced for the intelligent manufacturing process in Industry 4.0. With these methods, sustainability is high in this process (Figure 7).

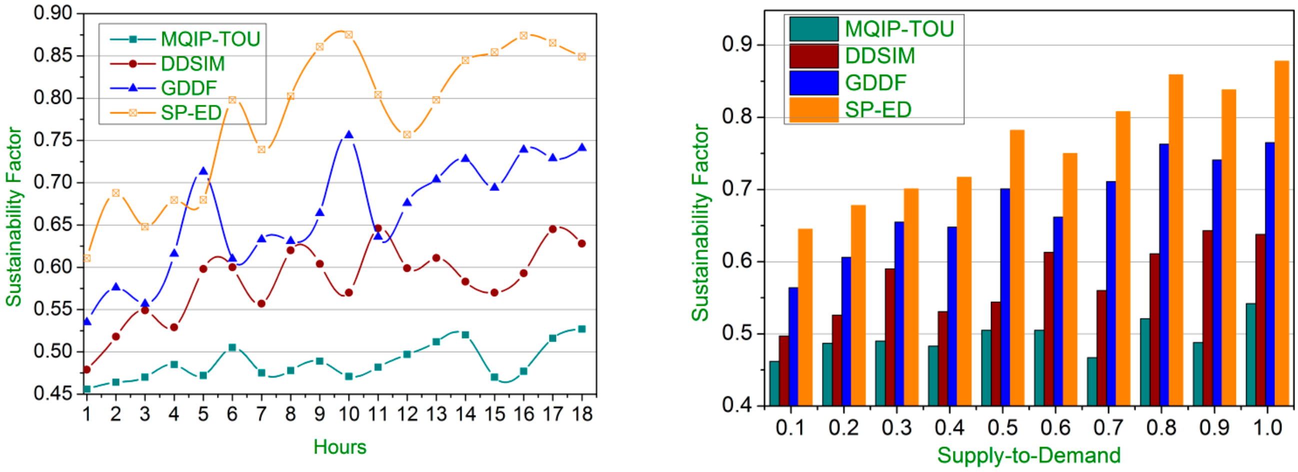

Figure 7. Sustainability factor.

4.2. Flaw Detection

Figure 8 depicts flaw detection during manufacturing and production in Industry 4.0 compared with the conventional method on which the proposed model has a high flaw detection rate. The flaw detection is high in this method using the FL technique, which uses the Ethereum blockchain records input. The production flaws are detected from FL, which verifies the consumption and distribution ratio during the manufacturing process. In this production flaw, if energy is inadequate, it can be verified, and further steps are taken to provide the needed energy. Thus, the redistribution process is carried out based on the blockchain records and the FL validations for the new manufacturing processes. The energy is redistributed based on its need, and a further process is carried out to modify the manufacturing procedure in the industry. The redistribution process is carried out to reduce the flaws and to make the energy last so long for the production process. Based on Equation (7), the production process flaws have been detected. This production flaw identifies the internal energy usage and the insufficiency of energy. It is used to check whether it satisfies the energy demand and sustainability. Through this FL validation process, the flaws in the production can be detected quickly, and further steps are taken to resolve them.

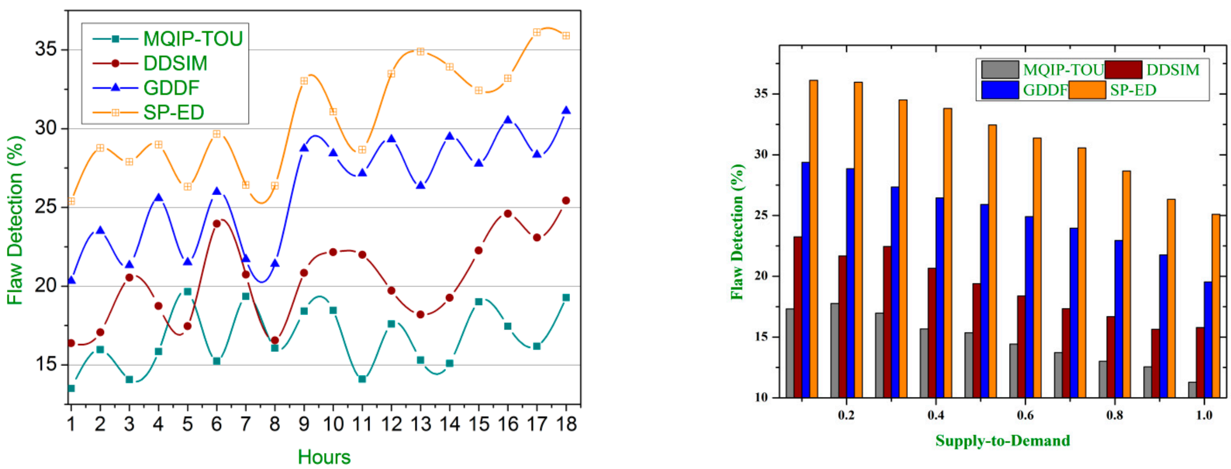

Figure 8. Flaw detection.

4.3. Demand Satisfaction

The demand satisfaction is high using Ethereum blockchain technology for manufacturing and flawless production. Ethereum blockchain is used to observe the internal and external demand obtained from the energy demand. It also checks whether the condition meets the required show and satisfies the needed directions. It is also used to enhance the energy's sustainability, which helps to satisfy the demand needed for flawless production. FL validates whether the sustainability of the energy lasts longer for the process based on the demand requirement. Both production distribution and demand satisfaction are identified by the FL technique, from which the flaws of the production are extracted during the manufacturing process in the industry. Ethereum blockchain monitoring is utilized for similar products, and demand satisfaction is completed in the production system. From Equation (2), demand satisfaction has been identified. The modification process is made from the blockchain records to improve the sustainability and production rate during manufacturing. The changes are made according to the blockchain records and FL validation (Figure 9).

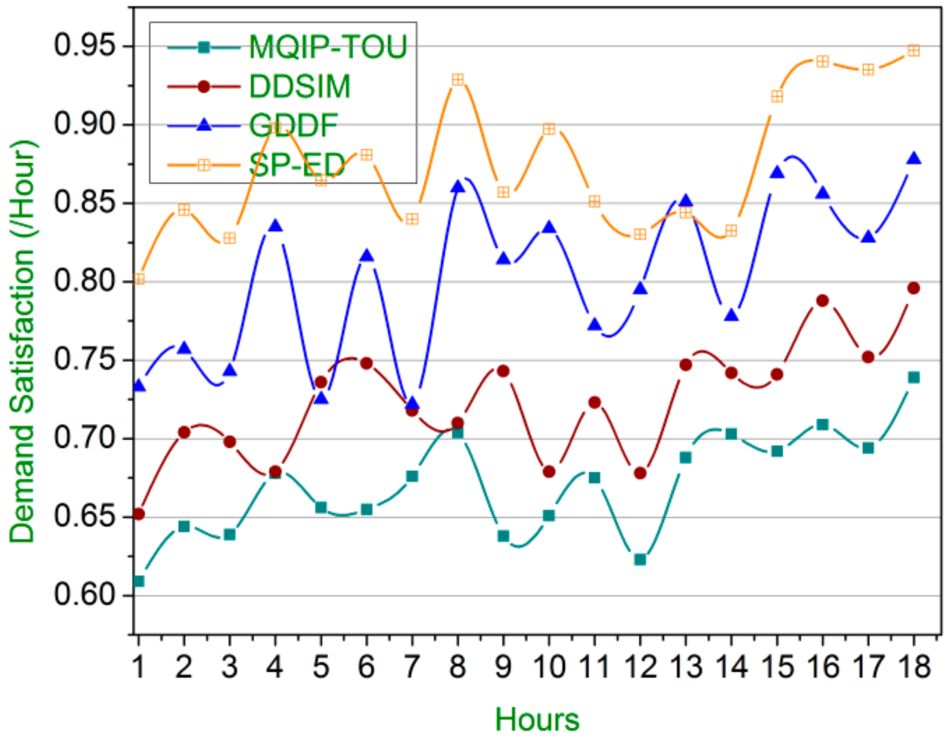

Figure 9. Demand satisfaction.

4.4. Modifications

The modifications are less in this method due to the usage of the required amount of energy for flawless production and the manufacturing process. Transformations are carried out to improve energy sustainability for the manufacturing process. Based on the blockchain records, the modification process is carried out. The modifications are carried out for the new production process based on the monitoring control output. It can help produce a productive manufacturing process in Industry 4.0. The improvements are made to the present method for the new manufacturing process, and the flaws are eliminated according to the demand requirement. This helps to enhance energy sustainability to meet production and demand satisfaction. The monitoring and condition satisfaction processes are identified using FL from two perspectives. The perspectives include demand allocation and production sustainability. From Equation (1), the modification process has been recognized. This process can be carried out to reduce the procedure of modification in the manufacturing procedure in Industry 4.0 (Figure 10).

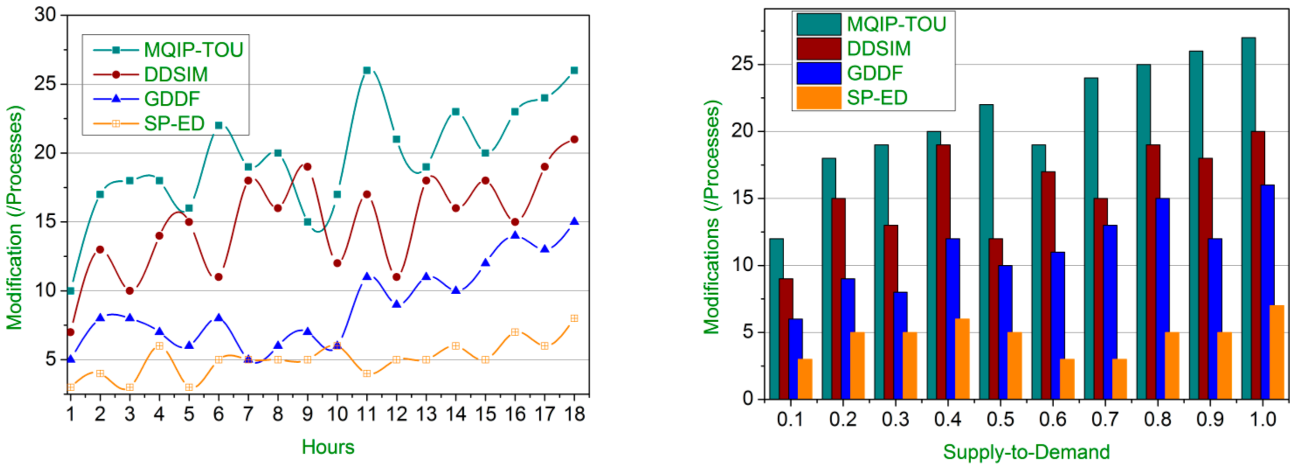

Figure 10. Modifications.

4.5. Detection Time

The time taken for detecting the flaws is recommended to be less in this method by using the Ethereum blockchain and FL techniques. By observing the internal and external demand, the blockchain technique uses this value as the input for FL. The production flaws are detected from FL; if there is insufficient energy, then it is said to be a flaw in the execution of the process. Energy sustainability checks how long the energy lasts to achieve the demand. The production system accompanies blockchain monitoring for lateral production and demand satisfaction. The observing and status gratification processes are approved using FL. The ineffectual conditions in prospects are manipulated using blockchain records. The Ethereum blockchain records reduce flaws in the new production by customizing the production plan according to the federated learning confirmations. Based on Equation (13), the detection time of marks has been identified. Using these processes, the time taken for the detection is less in this method for the flawless manufacturing procedures (Figure 11).

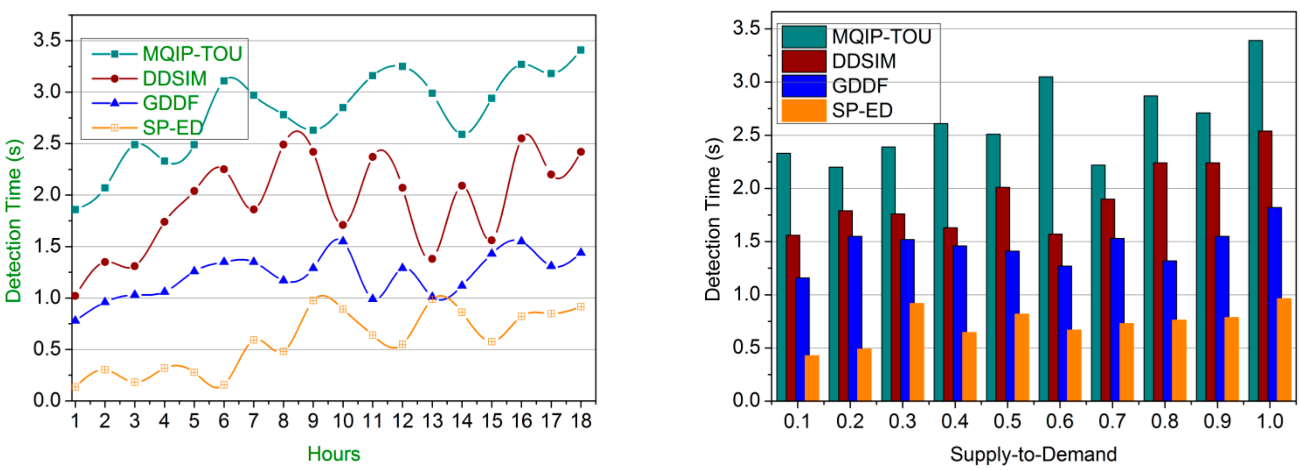

Figure 11. The detection time.

5. Conclusions

This article introduces and discusses the Sustainable Production concerned with External Demands method. This SP-ED method is designed to improve the efficacy of Industry 4.0 in energy production and distribution. The proposed method utilizes blockchain and federated learning concepts to improvise sustainability performances. The entire process is monitored, and the blockchain stores and processes detailed logs to identify production flaws. In this process, FL validates the sustainability and flaw detection for modifying the operations in consecutive operation cycles. The sustainability due to internal and external distribution demands is identified, and precise recommendations are provided. In the learning process, the maximum amount of achievable sustainability is predicted, and the performance is leveraged. The following learning process is instigated by considering the changes pursued in the production process using the recommendations. Therefore, the energy scheduling process is validated using joint blockchain and learning paradigms. Hence, sustainability is slowly leveraged across varying operation times and demands. The proposed federated learning and Ethereum blockchain model can achieve sustainability by 11.48%, flaw detection by 14.65%, and can reduce modifications by 11.11% and detection time by 10.46% for the varying energy supply-to-demand factor compared to DDSIM. The study's limitations are speed and scalability, a challenge identified for energy production and industrial applications. Future studies will examine the edge computing techniques for energy production for green innovation success in the industrial environment.

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