Smart Manufacturing for Smart Cities—Overview, Insights, and Future Directions

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With ‘smart’ being the order of the day, the shift in the landscape of a typical production-oriented manufacturing environment to a more data-oriented, automated and smart manufacturing is imminent. However, what is meant by smart manufacturing? And how can smart manufacturing contribute to a bigger picture by acting as enablers of smart cities? Given the paucity in literature that seeks to make sense in this direction, herein, first, six indices that represent or define a smart city are identified. Then, a holistic perspective of smart manufacturing is presented by collectively dwelling into the concepts of cyber physical production systems (CPPS) and industrial symbiosis—the recent and ongoing developments, applications, and relevant examples. In each subsequent section, the Review addresses how smart manufacturing contributes to smart cities, not just from a technology perspective, but also by satisfying the ergonomic factors and sustainability issues which are equally important indices that make up a smart city. A brief overview of Singapore as a smart nation and smart manufacturing hub is presented toward the end, along with highlights of a real-world smart manufacturing platform called the Model Factory and its relevant modules.

1. Smart Cities: An Introduction

According to statistics provided by the UN in 2018, the global urban population rose from 0.75 billion in 1950 to 4.2 billion by 2018, a 5.5-fold increase in nearly seven decades. Currently, this 4.2 billion urban population accounts for 55% of the current global population, and given the trend, the global urban population is expected to touch 68% of total population by 2050.¹² To keep abreast with this growing shift toward urbanization, the last decade witnessed a multitude of global projects across the USA, EU, Asia Pacific, and Middle East regions to cater to the needs of a futuristic urban population through the concept of “smart cities.”³⁴ Some of the popular programs include Smart Cities Initiatives by the USA,⁵ EU H2020 Smart Cities and Communities project,⁶ Smart Nation Program by Singapore,⁷ Global Initiative for Resource Efficient Cities (GI-REC) by UN,⁸ etc., to mention a few.

Existing literature shows that there is no single or standardized definition to the concept of a smart city.⁹ However, the central theme usually revolves around the application of information and digital technologies to provide intelligent and innovative solutions to the demanding requirements of an urban ecosystem including infrastructure, transport, healthcare, governance, and security.²⁰ The overall essence and motivation of a smart city is to facilitate the highest quality of life to its residents, while simultaneously optimizing the resources and energy efficiency, aiding the overall sustainability, social, and economic development of the city.

Given the fact that the concept of smart cities is constantly evolving, devising a single template to describe the various characteristic features of a smart city can be a challenging task.⁹ However, notable efforts have been made to determine and define a few salient features or indices of a smart city, published by research organizations as well as by consulting firms.¹¹ Both types of reports present commonalities in terms of indices, which are integral to smart cities and hence enable their acceptance with a degree of confidence. Some of the most notable and cited reports include Cities in Motion Index by IESE,¹² Smart Cities Ranking by Juniper Research,¹³ Top 50 Smart City

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Governments report by Eden-Oxd,[14] and the Smart City Index by IMD-SUTD.[15]

To benefit the readers from a quick overview, in Figure 1 we present the list of top ten global smart cities, based on the data points and research summary, as sourced from two popular reports, namely Cities in Motion Index by IESE[12] and the Smart City Index by IMD-SUTD[15] for 2019. Table 1 shows the list of six indices that were commonly reported by both the abovementioned reports and these very same indicators were used to develop the ranking of smart cities in this Review, based on the concept of weighted average.

Here, it is worth acknowledging that the evolutionary roadmap of smart cities is localized, self-centric, and determined by country-specific variables such as government stability and priorities, economy, population density, cultural norms, etc., to mention a few. For instance, Amsterdam aims to achieve sustainable economic development and efficient use of natural resources through its ongoing smart city initiatives. On the other hand, Singapore is striving to create safer communities and enhance the social and economic opportunities for its citizens through digital technologies, whereas Oslo is piloting over 50 projects involving climate-friendly buildings as its key smart city initiatives.

2. Smart Manufacturing as Enablers of Smart Cities

The manufacturing sector has been the primary catalyst for innovation, growth, and prosperity in countries across the globe and accounted for ≈15.6% of global GDP in 2018.[16] Most modern-day advanced economies accelerated their growth and development during the early industrialization era. However, with the emergence of the fourth industrial revolution in recent years, commonly referred to as “Industry 4.0.”[17] traditional manufacturing practices along with organizational and business models are being challenged and disrupted. Platforms such as cyber physical production systems (CPPS) and technologies such as Internet of Things (IoT), Artificial Intelligence (AI), digital twin, advanced robotics, 3D printing, etc.[17,18] within the “Industry 4.0” framework, are spurring the development of novel and advanced production and logistics concepts, organizational structures, and business models—all of which are expected to transform global manufacturing.

With smart being the order of the day, we will eventually evolve from modern cities to smart cities and transform the current best practices in manufacturing to smart manufacturing. While several reports have cited the role of smart healthcare,[19,20] smart transportation,[21,22] smart energy systems,[23,24] etc., as enablers of smart city, the role of smart manufacturing within the context of smart cities is not clearly defined nor understood. Undoubtedly, the current-age digital technologies, specifically the amalgamation of IoT–AI, are expected to be major drivers in this roadmap.[17,18] However, digitally aided manufacturing alone would not be able to meet all or several of key indices that define a smart city. How can then smart manufacturing satisfy the indices such as urban planning, environment, health and safety, citizen centric, etc., that are integral to a smart city? In simpler terms, what will be the role of smart manufacturing in smart cities or more subtly, how will they act as enablers of smart cities? These are questions of interest and require further insights, as there is paucity of literature that addresses these topics in a holistic manner. Thus, in this Review, we aim to fill this gap by comprehensively and collectively reviewing the concepts of CPPS and industrial symbiosis (IS) that will drive smart manufacturing and in turn propose how the effective implementation of the aforementioned concepts within the manufacturing framework will act as enablers of smart cities.

By nature of the topic, the role of smart manufacturing in smart cities is broad and diverse. However, understanding smart
manufacturing practices and application—though CPPS and IS and their eventual contribution to smart cities—necessitates a holistic perspective. Hence, in Section 3, we present an overview of CPPS and focus on Machine Learning (ML) applications in smart manufacturing with case studies. Here, we draw parallels between the technology and digital tools that are integral to a smart city as well as smart manufacturing. In Section 4, we reflect on the ergonometic aspects in smart manufacturing, which, though in nascent stage, ultimately corresponds to the citizen-centric and the health and safety indices of a smart city. We then shift the focus in Section 5 and introduce the concepts of IS in an urban environment, along with a brief review of recent works, to evaluate how they add to the sustainability criteria in terms of environment and urban planning of smart cities. Lastly, in Section 6, by taking Singapore as an example, we discuss the role of governments in driving smart manufacturing initiatives, such as the “Future of Production” (FOP) initiative under the Smart Nation Program Singapore. As an extension to the same, we also present a brief overview of a smart manufacturing platform, called the Model Factory, developed at the Singapore Institute of Manufacturing Technology (SIMTech), and highlight some of its main characteristic functionalities and modules.

3. CPPS and ML: The Digital and Technology Aspect of Smart Manufacturing

Much of the literature describes smart cities as an intelligent entity which integrates its physical assets and infrastructure with information and communication technologies (ICTs), the

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**Table 1. Smart city ranking indicators.**

| Indicators                        | Examples as listed by the reportsa) |
|----------------------------------|-------------------------------------|
| Urban planning and transport (U&T) | Residential buildings and facilities in residential complexes, location of commercial buildings, public transport, traffic congestion and parking |
| Digital technology (DT)          | Internet, free public WiFi hotspots, access to mobile phones, and CCTV |
| Environment (EN)                 | CO2 footprint, environmental performance index, recycling of plastics and wastes |
| Citizen centric (CC)             | Ample job opportunities, public welfare schemes, educational programs for children, and citizen participation in government decisions |
| Health and safety (HS)           | Ample hospitals and pharmacies, sufficient sanitation, public safety, crime rate, and mortality rate |
| Government and leadership (G&L)  | Open data platform on government policies and decisions, corruption index, online processing of government-related documents, initiatives for social, public, and economic welfare |

*a) This list is not exhaustive and is presented to give a basic description of the indices reported in the reference reports.*
confluence of which is popularly also known as CPS. These CPS continuously source and store relevant data (which eventually evolve into big data) and ultimately leverage this data to drive efficient urban operations, satisfy the needs of its residents, and ensure the demand and supply of resources in the present and future.\textsuperscript{[2,23]} Drawing parallels and inspiration from this concept, the application of CPS in manufacturing is referred to as CPPS which integrate physical resources and operation technology (OT) with information technology (IT) through all levels including production systems, individual machines, supply chain and logistics, to increase the efficiency, productivity, and safety in manufacturing operations.\textsuperscript{[26,27]} Within the context of “Industry 4.0,” CPPS is considered to be the core and main driver toward the transformation of smart and automated manufacturing.

3.1. Overview of CPPS

The notion of intelligent manufacturing has existed since the 1980s as the intersection between AI and manufacturing. However, more recently, with the eminence of “Industry 4.0,” the concept of CPPS and technologies such as data-driven analytics, AI, IoT, and cloud computing, to mention a few, have found surged interest within the manufacturing domain and are driving the modern generation of intelligent and automated manufacturing practices.\textsuperscript{[27,28]} CPPS are synonymous to the building blocks of an automated manufacturing environment. These multifaceted and complex systems aim to integrate the real-world, dynamic physical process and the cyber world through the communication–computation–control (3C) loop, thereby enabling real-time sensing, flow, and feedback of information to ensure safe, reliable, and efficient operations in a production environment as well as in supply chain management.\textsuperscript{[27,29]}

At the heart of the CPPS lie the computational models which can be purely mechanistic in nature or data driven or hybrid, whereas IoT ensures the steady and uninterrupted flow of information (data) from one entity of the CPPS to the other. A detailed review of IoT and their significance within the “Industry 4.0” framework are covered elsewhere\textsuperscript{[30,31]} and are not the scope of this article. Given the significance of big-data and data-driven modelling in the context of “Industry 4.0,” in the next subsection, we focus purely on the application of ML (as the computational or modelling approach) in manufacturing. Figure 2 shows an overview and flow schematic of the CPPS.

3.2. ML in Manufacturing: Concepts and Applications

3.2.1. Basics of ML in Manufacturing

ML, a subset of AI, is an applied computational technique with the ability to process large, complex, and multidimensional data. It is able to learn from existing patterns within the data and build models to make predictions for a given process under consideration;\textsuperscript{[28,32]} thereby aiding enhanced and informed decision-making. ML algorithms are broadly classified into three types, supervised, unsupervised, and reinforcement learning. We limit the scope of this Review to supervised and unsupervised learning as these algorithms find common applications as well as implementation in the manufacturing sector.\textsuperscript{[28]} A supervised learning algorithm trains on a set of input features (independent variables) and target labels (dependent variables) to devise a mapping function to predict the target label, on encountering new unlabeled data.\textsuperscript{[33,34]} These algorithms are known as supervised as they utilize a training dataset to learn the required weightage factors to be given to an input feature, such that they predict the target label with minimum deviation from the actual. Supervised ML algorithms can be applied to classification as well as regression problems. While a classification problem has a discrete value as its output, a regression problem solves for a real number as its output. From a smart manufacturing perspective, supervised algorithms can be used for process or quality monitoring and prediction in a shop floor, where the set of input features could be process parameters such as temperature, pressure, feed flow rates, density, etc., whereas the target label could be yield or quality of the final product. Supervised learning can also be used to estimate the health of machines in a shop floor via predictive maintenance (PdM). The set of input features in this case could be similar to the ones aforementioned (process related) except that the target label would be binary (0 in case of normal operation and 1 in the case of machine breakdown or failure). Depending on the type of algorithm, i.e., either regression or classification, different types of metrics exist to gauge the accuracy of the model\textsuperscript{[35,36]} and thereby improve the performance of the ML model either during cross validation or during subsequent training postiterative feature engineering.

Unlike supervised ML algorithms, unsupervised ML algorithms are mostly used to learn the basic structure of the data, i.e., to identify salient, inherent, and causal or hidden patterns among the set of input features\textsuperscript{[34,37]} that would elsewise not be conceivable by simple inspection. More than often, these algorithms are used to either cluster homogeneous subgroups within a high-dimensional dataset or reduce the dimensionality without significantly affecting the variance determined by the individual input features in the original dataset. Within the manufacturing domain, clustering approaches can be used, for instance, to cluster production process-related data to undermine hidden patterns or subgroup process variables or in supply chain and logistics to subgroup vendors to minimize supply chain risks or end users (customers) with similar market characteristics including pricing, number of items purchased, average transaction value, etc.;\textsuperscript{[38,39]} to mentions a few.

Practical applications of ML algorithms in a manufacturing setting can be implemented by exploring and making use of data that usually sit on the manufacturing execution system (MES) or supervisory control and data acquisition systems (SCADA). Reports cited in the literature broadly classify the application of ML within manufacturing under three categories: process monitoring and control, PdM and production, and supply chain planning. To this context, a review on the recent contribution of ML in the aforementioned categories is presented in the following sections and a summary of the same is shown in Table 2.
interdependent of each other, thus generating complex, dynamic, and stochastic conditions during the process of product life cycle. Conventional approaches such as lean manufacturing and six sigma,\textsuperscript{[54]} discrete-event,\textsuperscript{[55]} and agent-based\textsuperscript{[56]} methods have been applied for operational excellence in a shop floor. While these methodologies offer their own advantages, these are more than often nongeneric (i.e., applicable only to a particular product design or manufacturing process) and fail to capture the intricate complexities and inter-relation among the various process and operational parameters in shop floor. Data-driven ML approaches, on the other hand, which primarily rely on data rather than the physics and thermodynamics of these processes, offer a more generic and computationally faster approach for sustainable design, process monitoring, quality control, and effective system integration in a manufacturing environment.\textsuperscript{[37,57]}

Lv et al.\textsuperscript{[40]} sourced data from the ERP system and devised an artificial neural network (ANN) and neighborhood component feature selection-coupled ANN (NCFS-ANN) using a set of 40 input features to predict the scrap rate and material feeding (target labels) during the production of printed circuit boards and observed that the performances of the NCFS-ANN were better than the standalone ANN model. Li et al.\textsuperscript{[41]} presented an online monitoring approach to predict the surface roughness of 3D-printed parts during the fused filament fabrication process using the process data sourced from in situ sensors. In contrast to most studies, the authors devised an ensemble algorithm comprising random forest (RF), classification and regression tree (CART), random vector functional link (RVFL), ridge regression (RR), support vector regression (SVR), and adaptive boosting (Adaboost) in their study which was found to have better prediction performance than the individual ones. Caggiano et al.\textsuperscript{[58]} proposed an ML approach for online fault detection (via image processing) to precisely identify defected components in selective laser melting (SLM). The deep convolutional neural network (DCNN) algorithm developed in this study was able to characterize layer-wise images of the SLM process and thereby identify defects induced by process nonconformities with a classification accuracy as high at 99.4%. The author used a multitude of ML algorithms and observed that ANN, RF, and k-nearest neighbors (k-NN) closely matched each other’s performance in elasticity prediction whereas lasso linear regression (LR) was identified.
as the best for density prediction. To showcase the true merits of CPPS and ML, Min et al.\cite{44} proposed an intelligent framework to increase the yield of light oil (gasoline and diesel oil) in a petrochemical production unit with an ML-based control optimization method. In this study, the authors extracted historical data of 410 input features (40 control variables and 370 regular process variables) from the plant SCADA and, by applying Pearson’s correlation coefficient (PCC), reduced the final set of input features to 100. Four tree-based supervised algorithms, including RF, AdaBoost, extreme gradient boost (XGBoost), and light gradient boosting machine (LightGBM), were trained on the historical data where it was observed that the LightGBM model gave the most accurate prediction. This model was then utilized to devise the digital twin of the production system and eventually integrated online with the SCADA, for real-time recommendations of the control system to the plant operators.

### 3.2.3. ML for PdM

The estimation of the health status or conditions of equipment and machines present in a manufacturing or production environment has been an active area of research\cite{33} as machines with faulty health conditions and frequent breakdowns affect the operational process time. Therefore, the equipment’s faulty states and subsequent breakdowns have to be identified or predicted well in advance and should undergo timely maintenance to avoid unnecessary or unplanned shutdowns in the production processes. The data collected and stored by industrial systems contain information about normal and abnormal events along any production line and the corresponding “alarms” that are generated\cite{33,59}. ML algorithms can leverage from these data and upon appropriate analysis can aid in strategic decision-making, by timely fault identification and breakdown prevention, maintenance, and increased shelf life of machines in shop.

| Sl. No | Industry | No. of datapoints | Input features | Data source | Target variables | ML algorithms\(^a\) | Reference |
|-------|----------|-------------------|----------------|-------------|-----------------|-----------------|----------|
| 1     | Printed circuit boards | 30 117 | 40 | ERP | Scrap rate and material feeding | ANN | [40] |
| 2     | 3D printing | 104 | 40 | Sensors | Surface roughness of 3D-printed materials | RF, SVM, CART, RF, and AdaBoost | [41] |
| 3     | Glass | 24 858 | 24 | ERP | Density of glass oxides | RF, k-NN, ANN, SVR, and Lasso-LR | [42] |
| 4     | Glass | 8519 | 24 | ERP | Elasticity properties of glass oxides | RF, k-NN, ANN, SVM, and Lasso-LR | [42] |
| 5     | Chemicals | 260 | 17 | Industrial dataset | Purity of produced terephthalic acid (PTA) | ELM | [43] |
| 6     | Hydrocarbon | – | 410 | DCS | Yield of light oil | RF, AdaBoost, XGBoost, and LightGBM | [44] |
| 7     | Semiconductor | 3671 | 31 | – | Breaks in tungsten filament used in ion implementation | SVM and k-NN | [45] |
| 8     | Additive manufacturing | 206 | 7 | Sensors | Cluster the health condition of the machine | k-Means clustering | [46] |
| 9     | General | 530 731 | 15 | Sensors & PLC | Activity states of a spindle rotor in a cutting machine | RF classifier | [47] |
| 10    | Milling | 167 | 26 | Operational data | PdM of milling cutting tool | Logistic regression (LogR), decision trees (DT), boosted DTs, and ANN | [48] |
| 11    | Aerospace | – | 21 | NASA dataset | RuL of turbo fan engine | LR, DT, SVM, RF, k-NN, k-Means, GBM, and AdaBoost | [49] |
| 12    | Semiconductor | 22 465 | 24 | – | Predict the probability of a part failing before n wafers are processed | LogR, RF, XGBoost, and DL | [50] |
| 13    | Semiconductor | 18 532 | 41 | MES | Manufacturing lead time | RR, lasso regression, MARS, DT, bagged DT, RF, boosted RF, SVM, k-NN, and ANN | [35] |
| 14    | Aerospace | 36 677 | 33 | MES | Delayed product deliveries | SVM and DT | [36] |
| 15    | General | 5600 | – | Simulations | Scheduling production order | SVM | [51] |
| 16    | General | 10 000 | 28 | Simulations | Production flow time | ANN, RF, and XGBoost | [52] |
| 17    | Steel | 63 000 | 27 | Industrial dataset | Tensile strength and plasticity | LR, k-NN, SVM, DT, GB, RF, and XGBoost | [53] |

\(^a\)The algorithm highlighted in bold represents the best performing algorithm in the respective case study.
floor, increased production, and improvement in operator safety.\cite{59,60}

Susto et al.\cite{45} proposed a multiclassifier PdM methodology to identify breaks in tungsten filament used in ion implementation, a critical unit operation in semiconductor fabrication and manufacturing. Their study involved the comparison of SVM and k-NN algorithms and it was concluded that the SVMs outperformed the k-NN algorithm and that ML-based PdM consistently outperformed preventive maintenance approaches. By exploring patterns in the process data sourced from historical database, Uhlmann et al.\cite{51} devised an unsupervised k-Means clustering approach to subgroup the health condition of a machine tool into four categories: normal operations, faulty conditions due to pressure systems, faulty conditions due to protection gas, and faulty conditions keeping the machine in a standby mode. In a related study, Amruthnath and Gupta\cite{61} collected the vibrational monitoring data of exhaust fans over a 4 h interval for 12 days and were able to group the exhaust fans as healthy, warning, and faulty state, using three clustering algorithms including k-Means, C-Means, and hierarchical clustering with identical clustering performances. In an exhaustive study, Paolanti et al.\cite{41} extracted the data of a cutting machine from sensors, programmable logic controllers (PLCs), and the database including 530731 data points, comprising 15 input features (with details of maintenance, repair, process conditions, machine faulty history, etc., to mention a few). They then employed RF classifiers to predict the activity states of a spindle rotor in a cutting machine where the algorithm was able to predict the activity state of the spindle rotor with an overall accuracy of 0.95, along with the precision and recall of 0.94 each, respectively. Butte et al.\cite{50} proposed a biphasic PdM approach in semiconductor manufacturing. They first devised a classification problem to predict the probability of a part failing before ‘n’ wafers were processed (n = 25). Their dataset included 21 tool sensor data, three process recipes, and wafer count of the critical equipment, which was randomly split into 80:20 ratio and subjected to ML classifiers including logistic regression, deep learning, RF, and extreme gradient boost for failure prediction. The deep learning algorithm showcased best performance on the test data. Once the failure event was predicted, they developed regression models using an ensemble algorithm of the three base algorithms (deep learning, RF, and extreme gradient boost) to predict the remaining useful life (RUL) until next failure. The ensemble model was able to outperform each of the base model in terms of reduced variance and inaccuracies, thereby making the PdM system more robust. A detailed review along with most recent case studies and application of ML in PdM is presented by Carvalho et al.\cite{33}

3.2.4. ML for Production and Supply Chain Planning

Most manufacturing industries are characterized by highly complex and stochastic conditions during production (internal) and simultaneously subjected to volatile and dynamic supply chain conditions (external). ML algorithms have the ability to learn from historical or real-time data to predict events, which can help in informed decision-making in the domain of production and supply chain planning, scheduling, and control. A detailed review on ML applications to production planning and control is presented in a recent article by Cadavid et al.\cite{39}

Lingitz et al.\cite{15} used the historical data from the MES for a period of 2 years and conducted a comparative evaluation of 11 supervised ML algorithms to predict the lead time in a semiconductor production facility. Among the various algorithms evaluated, including LR, RR, lasso regression, multivariate adaptive regression (MARS), regression tree (RT), bagged RT, RF, boosted RF, SVM, k-NN, and ANN, it was observed that the RF algorithm gave the best prediction whereas ANN had the least predictive ability. Baryannis et al.\cite{56} developed and evaluated the risk prediction framework for supply chain risk management in an aerospace manufacturing supply chain. With details of a particular supplier for 36 677 product deliveries collected from the MES for a 6-year period, the authors used two binary classifiers, namely SVM and DT, to predict whether future deliveries of a particular supplier would be delayed or not, where the result indicated that the performance of the SVM classifier was better than DT in terms of higher precision and recall. Liao\cite{31} used an SVM to construct the intelligent dispatcher that replaced the existing dispatching rule methodology to schedule jobs at each decision point for parallel machines. A systematic design of experiments (DOE) was first performed to generate 5600 scheduling scenarios and the SVM model was then made to learn from the scenarios to develop an intelligent task comparator for scheduling jobs at each decision point. A comparison of the scheduling prediction by the SVM closely matched simulation results and proved good generalization capability. In a related study, Murphy et al.\cite{52} designed a series of discrete-event simulations to mimic the real-world production process of a highly dynamic flow shop, by including behaviors such as rework, machine set-up, machine repair time, and machine downtime. With a total of 28 input features (describing the job and shop characteristics), 10 000 simulations were devised and ML models including ANN, RF, and XGBoost were trained and compared to predict the flow time under different dispatching rules. A comparative evaluation of the ML algorithms yielded ANN as the best serving ML model and in general the ML algorithms outperformed the conventional due-date assignment (DDA) rules which were also used for flow time estimation.

3.2.5. Other Potential Applications

The benefits offered by ML in manufacturing are primarily witnessed by improvements in process efficiency and performances, as discussed in preceding sections. Apart from those applications, ML also offers benefits in terms of asset life cycle optimization,\cite{62} in the rapid progress and maturity of new manufacturing paradigms such as nanomanufacturing and additive manufacturing through the concept of inverse design\cite{63} and customer-centric product development\cite{64,65} which are briefly discussed.

ML-based predictive models have played a crucial role in the determination of how various operational and process parameters affect the life cycle of industrial equipment, machines, as well as products. To this extent, based on the determination of significant features from these models (often referred to as feature importance analysis), life cycle assessment and
optimization of the machines and products have steered the attention of the manufacturing domain based on the combined ML and life cycle assessment (LCA) framework. The discovery of high-performance functional materials has garnered huge interest in various manufacturing industries including metals, polymers, ceramics, and semiconductors. While extensive efforts are devoted toward accelerating and facilitating the design and manufacturing of these high-quality and low-cost products, supervised ML has attracted considerable attention, as it can provide rational guidelines for efficient material exploration without time-consuming iterations. Within the context of customer-centric product design, also referred to as smart design, the user demands, preferences, and demographics can be quantified from historical databases based on product quality review (either from the company’s product review site or e-commerce platforms), and make-to-order (MTO), personalized products can be designed by manufacturing industries using supervised as well as unsupervised algorithms. This capacity to harness user-centric data provides opportunity to manufacturers to streamline the design processes, promote product innovations, and develop customized products for end users.

3.3. Section Summary and Key Challenges

Over the past decade, the drive and evolution toward modern manufacturing practices has been brought about by the so-called fourth industrial revolution “Industry 4.0,” which aims at connecting the physical assets including humans in real time throughout the production and supply chain network with ICT technologies. CPPS-aided manufacturing thus draws analogy to that of a smart city, which is built on the notion of an organized entity where its physical, social, and economic infrastructures are integrated with IT to leverage collective intelligence of the city through exchange of data, for efficient urban operations, services, and quality of life, except at a more local scale and with lesser networks. Given the synergies between the underlying principles that define a smart city as well as smart and data-driven manufacturing, CPPS aided by AI and IoT technologies within the manufacturing framework would serve to satisfy of “digital and technology” indices of smart cities.

However, there are multiple limitations that hinder their exclusive implementation and must be considered as well. First, the existing data extraction methodologies in manufacturing industries are not designed for ML-based analytics, given the fact that a multitude of physical assets (machines and field instruments) are subjected to different communication interfaces and protocols including TCP/IP, Message Queuing Telemetry Transport (MQTT), or related ones. This demands the need to uniformize data extraction and transfer protocols. Even when the aforementioned shortcomings are addressed, some issues would still persist, the main ones being limited bandwidth in the case of a decentralized system and insufficiency of latency time, including both low and high latency. These seriously limit the application of CPPS and ML-based predictive analytics for real-time applications.

A general premise in ML is that these algorithms tend to learn with more data and thus depend on the scale and quality of datasets. Though much of the data from a shop floor origin is structured, multimodality and time-series alignment of the various input features data, the intermittent scenario of unstructured data in the case of logistic-related datasets derived from the MES renders the need for task-specific feature engineering or regularization to improve the performance of ML. Moreover, real-world time-series data are quite skewed in their distribution which presents another challenge in the form of class imbalance. Least to mention, given the multitude of ML algorithms, the selection of the most appropriate one for a complex manufacturing process remains a challenge, as there is no universal rule that determines such selections, and multiple algorithms are often trained and tested before the one with best accuracy and generalization ability is selected. This limitation can be addressed through lifelong learning, where the selected algorithm continuously trains and learns from historical data and evolves over a period of time.

4. Citizen Centric and Safety Aspects in Smart Manufacturing

Factoring the human element within the smart city framework deserves its own space and recognition, to ensure prolonged success and sustenance of smart cities. While it is essential to empower the citizens such that they contribute to the development of smart cities through active participation and effective engagement, it is also equally important that these citizens are provided with ample opportunities to leverage socioeconomic benefits and experience an improved quality of life.

Within the scope of “Industry 4.0,” the shift in the landscape of a typical manufacturing shop floor, i.e., from very hands-on, manual labor, interpersonal communications, and judgments or actions primarily driven by human experience, to a very decentralized environment with CPPS including advanced automations, cloud computing, IoT–AI-enabled technologies, driving actionable insights into the manufacturing process is forthcoming. This in turn would drive major improvements benefitting the manufacturing workforce from being production centric to data driven and tech oriented in three distinctive ways, which are as discussed below.

4.1. Training and Continued Professional Development

The drive toward CPPS-enabled smart manufacturing is anticipated to replace many aspects of conventional manufacturing practices including both technical and organizational. David et al. proposed that, for the successful realization of the Industry 4.0 paradigm in a socially sustainable manner, technological transformations along with training and development programs for their workforce would be essential. They introduced the concept of an “Operator 4.0” and presented the ideology that through training and dynamic interaction with CPPS, the manufacturing workforce would become smarter operators. The research findings of Dworschak and Zaiser inferred that the degree of CPPS implementation in enterprises has been relatively low, either due to lack of the relevant technical skills in the existing workforce or due to lack of technology forecasting by decision-makers. Their study concluded that the timely identification of skill gaps and training measures to address this gap, as well as competency to anticipate technology
transformation by the higher management, was the key to drive technological innovations in smart manufacturing.

The concept of learning factories offers a promising outlook in this direction to aid the competency development across various levels in such complex production environments. These learning factories have the capability to provide realistic training scenarios that mimic an actual production environment and can be used for operator training, performance and competency evaluation, and testing, and demonstration of new technologies and platforms. To this context, Block et al. emphasized on the lack of IT skills by engineers and production workers in manufacturing environments and presented a holistic framework in form of a learning factory module. Within the training module, the trainees developed a CPPS for an assembly line from conception to implementation and were trained on how to select the hardware and software components for a modular, decentralized, and cross-deployable CPPS. A detailed discussion on insights as well as the outlook of learning factories in manufacturing is presented by Abele et al. This change in demographics would necessitate the subsequent training and adoption of these technologies by aged, apprentice, and disabled workers, who form a formidable portion of the total workforce in any manufacturing industry, thereby bringing forth the scope of continued professional development.

4.2. Work Organization and Design

Within the scope of “Industry 4.0,” the implementation of a sociotechnical approach to the work organization will provide the workforce with profound work-related challenges along greater sense of responsibility and job satisfaction. The transformation into smart and automated manufacturing will demand new product and process design as well as engineering philosophies driven by a smart workforce, thereby enhancing and augmenting the human’s physical, sensorial, and cognitive capabilities. The combination of CPPS and human workforce is anticipated to create what is also referred to as hybrid production systems known as Human-in-the-Loop (HitL) and Human-in-the-Mesh (HitM), pertaining to the human–CPPS interactions for increased flexibility in manufacturing, have been reported in recent works. The HitL combines data-driven models with human knowledge and actions, augmenting the advance of machine intelligence, and yet proposes the human factor as the first in line and master of the production environment, supervising and adjusting process set points, detecting alarms and abnormalities, driving corrective and required actions, etc. In contrast, the HitM model describes the role of humans with minimalistic intervention and the CPPS as the drivers of production environment. In a related study, Pacaux-Lermoine et al. proposed the human-centered design for an intelligent manufacturing approach to understand the role of human–machine interactions in a CPPS. They suggested that the workers on the shop floor would have a better control and decision-making ability, aided by the CPPS, and would have sufficient response time to react under unexpected and undesirable conditions and thus lead to the improved performance of complex and conflicting production objectives while simultaneously easing the workers’ workload and stress factor.

4.3. Safety, Security, and Flexible Operations

A smart manufacturing environment is not only designed to make production processes more automated and efficient, but also to bring forth the scope and convenience of flexible or remote work in a decentralized manufacturing ecosystem driven by CPPS, while ensuring safety and risk assessment in production facilities. A detailed review on the focus for occupational health and safety within the context of evolving manufacturing practices is provided by Schulte et al.

Palazon et al. suggested that wireless sensor networks when effectively and appropriately integrated with the physical systems would substantiate the autonomous and intelligent platforms in manufacturing settings and preventing accidents. This was further supported by Gisbert et al. as the authors maintained that digital technologies such as IoT and AI have the capability to detect or predict operational hazards and dangers in the workplace and guarantee the reliability of such integrated systems and separate remote centers to monitor their function, and performance has to be implemented. Kuschnerus et al. claimed that while the CPPS offers the promise of adapting to dynamic conditions in industrial process automation, these systems should also benchmark safety limits for various processes, such that operational hazards and risk reduce to a tolerable level, as specified by standards (e.g., IEC 61508). Peruzzini and Pellicciari proposed that wearable and handheld digital tools such as smart phone and smart watches of the plant operators when linked to CPPS would create novel and unique opportunities to configure the daily manufacturing practice operations in accordance with the worker’s behavior and stress level. However, this ideology could be challenged given the data sensitivity-related issues. In a related study, Hummel et al. mentioned that key performance indicators (KPIs), representing the status of a production system as well as the ergonomics data of the workers, could be leveraged by other departments of the company, for planning alternative or backup activities, depending on the requirements.

4.4. Section Summary and Key Challenges

The role of the human workforce will be decisive in this transformational journey toward “Industry 4.0,” and their adaptation to the smart and automated manufacturing environment in an efficient and effective way would depend on the tangible and intangible benefits offered by “Industry 4.0.” To this cause, the opportunities provided in terms of continuous professional development, advanced training, including IT and AI skills to upgrade the competency of the new-age manufacturing workforce, and organizational tasks involving data-driven decision making would ensure a greater sense of job satisfaction, responsibility, and contribute to the “smart citizen” aspect of a smart city. Likewise, decentralization and remote access of manufacturing units via CPPS, predictive analytics to forecast machine breakdown, failures or unplanned events, and greater
Automation of repetitive tasks will minimize accidents prone in a shop floor, thereby fostering safer working space and conditions, and thus satisfy the “health and safety” aspect of smart cities.

No transformation in the manufacturing domain should be contemplated without discussing the full potential implications on its workforce. While the merits of an autonomous and decentralized manufacturing environment are claimed in terms of improved competency, and learning opportunities to the workforce, along with safer working conditions, the transformation toward the smart manufacturing paradigm has to address a few points. Increased efforts in the form of interdisciplinary research is essential to improve the integration of human labor with autonomous systems, along with the need to develop new standards or modify existing ones, to adapt to the next-generation manufacturing practices and technologies. The configuration and the efforts required to operate the CPPS must be adapted to the cognitive skills and physical capacities of the workers. With anticipated organizational transformations such as HitL, modeling of human behavior, stress, and awareness levels via adaptive interfaces and emotion sensors have to be developed. A thorough research focused on occupational hazards and risks at all levels of production, improving the social responsibility of businesses, and the effective usage of current-age digital technologies would be imperative.

5. Industrial Urban Symbiosis: The Sustainability Dimension of Smart Manufacturing

Cities comprise residential, commercial, and industrial areas which are dependent on the supply of resource networks including water, energy, minerals, petrochemicals, finished products, etc. for sustenance. Within the framework on a city, urban metabolism (UM), can be defined as the methodical study of the flow of resources, including their source of origin, transformation, consumption, and disposal postusage. Figure 3 shows the schematic of UM with its generic input (I) and output (O) flows, internal flows (Q), and storage (S) and production (P) of different resources (B, M, W, E). The concept of circular economy aims to create closed-loop systems for physical resource flows by applying the principles of reusing, sharing, repairing, remanufacturing, and recycling. The implementation of a circular economy in the UM can be a fruitful strategy for value creation and urban planning of smart and sustainable cities.

The ideology of a circular economy within the manufacturing sector has garnered wide research interest in recent times, primarily through the context of IS. An IS is an integrated systems approach, in which the resources classified as underutilized, waste, or byproducts, by one industry, are leveraged as a resource by another. This practical approach aims to enhance resource utilization and reduce waste generation and greenhouse gas (GHG) emissions via exchange of material, energy, and byproducts between different processes within a manufacturing or production site (microscale) or among intraindustries (macroscale). A successful implementation of IS is demonstrated at the ecoindustrial park (EIP) in Kalundborg, Denmark, which consists of a power plant, different greenhouses, a pharmaceutical plant, a refinery, and the municipality, all of which symbiotically exchange resources such as heat, water, and materials, thereby positively driving the overall resource efficiency within the industrial park.

The concept of IS within cities is described using different terminologies in the literature. The term urban symbiosis (UrS) is referred to in many publications as an extension of IS to describe manufacturing sites in close proximity with cities, where the byproducts (wastes) from the cities (or urban areas) are used as alternative raw materials or energy sources in the industrial operations. The fundamental difference in the context is the location and the scale of exchange between functions. The conceptualization of IS within urban contexts allows for the development of a circular economy framework within UM. Figure 3 depicts the schematic of a common IS and IIoT setup and representing the generic input flow (I), output flow (O), and internal flows (Q) along with the storage (S) and production (P) of different resources such as biomass (B), minerals (M), water (W), and energy (E). This information when collected and stored can be used for resource flow assessment and matching, i.e., matching of the demand with the supply, using various tools and platforms.
between IS and UrS is brought about by Chen et al.\[110\] where the authors suggest that IS exchanges byproducts and wastes among industries only, whereas UrS describes the interaction among urban municipalities and local industries such that municipal solid waste (which would otherwise be disposed or incinerated) is used as the input by the associated manufacturing industry. Other works\[111\] integrate the terms IS and UrS as IS/UrS, to maximize the symbiotic advantages. While IS/UrS primarily focuses on symbiosis of specific entities (i.e., manufacturing companies, urban waste flows), works on UM focus on understanding, analysing, and engineering of UM at a global system level (system of systems). The latter does not necessarily utilize the term symbiosis, but the essence and overall implications remain the same, i.e., to foster the ecoefficient exchange of resources within cities.

Numerous tools used for the planning of UM have been reported in the literature\[112,113\] which are largely utilized to identify resource exchange opportunities between urban and industrial systems and are thus highly relevant for identifying and utilizing resource interfaces within the smart city. These tools are becoming increasingly smarter in the process of identifying and matching resource flows and thereby fostering the realization of symbiotic relations in resource-demanding entities.\[114,115\] In this section, we present an overview of the conventional as well as smart approaches, specific to IS, IS/UrS, and UM, as they find significance in manufacturing practices and simultaneously contribute to the urban planning and environmental dimension of smart cities.

5.1. Urban IS: An Overview

Neves et al.\[116\] comprehensively reviewed and investigated the interactions between IS and UM (IS/UrS) and specifically stressed on the economic and ecological advantages witnessed by the existing IS/UrS project implementations across the globe. The authors primarily investigated the various methods to analyze the networks of IS and quantify their respective impacts and suggested that the potential for IS continuously increased given its positive impact on UM from an environmental perspective. However, understanding the social implication of IS/UrS was a challenge, and to this context, the need for viable methods to analyze the social impact of IS was also stressed. Fraccascia\[117\] presented a systematic review on IS in urban areas and identified that a minimum stable amount of waste was critical for creating economically viable relations within the IS context. The author emphasized that a stable waste disposal system would play a decisive role for the successful acceptance of IS, and should availability of waste resources be lower than the minimum quantity required, companies would not be willing to implement IS. The study also focused on the significance of transparent platforms to match supply and demand among the participating manufacturing companies and the implications of economic investments required to advance the actual resource exchange.

Sun et al.\[118\] presented a quantitative analysis to evaluate the energy savings and emissions reduction potential through IS/UrS implementation in the city of Shenyang. They proposed an IS/UrS system which included a municipal waste sludge treatment facility, that would supply energy (via incineration) and recycle papers, plastics, and waste tyres to a variety of manufacturing sites. Though the supply of energy presented technical and financial challenges, under optimum conditions, carbon emission reduction by 1.3% and energy recovery of the order $8 \times 10^6$ GJ were proposed. Butturi et al.\[119\] proposed various schemes for the integration of renewable energies in EIPs. Four key aspects toward the implementation of collective energy strategies were outlined, including the collective green energy procurement, usage of exchange and recovery processes, collective energy production, and the share of infrastructure and services. Smart infrastructure and energy management platforms were identified as central enablers to this objective. The authors also advocated the analysis of energy symbiosis between industrial and urban areas as combined single units rather than as separate entities.

Herczeg et al.\[120\] investigated the operational challenges in symbiotic exchange between manufacturing companies in urban systems and accentuated the necessity for a central information exchange system, enabling automatic identification of matching resources and their seamless exchange or allocation. The authors also addressed the fact that temporal variations in the supply and demand of resource changes have not been addressed with reference to IS and concluded that such volatilities—induced by variations in primary production activities and short-term demand variations—present substantial challenges to the efficiency of the symbiotic network. Capelleveen et al.\[121\] reviewed information systems facilitating IS and identified that collaborative internet-based platforms would serve as key enablers of IS. Based on three attributes, namely target group, support provided, and technologies used, a typology of six different concepts was developed. Furthermore, the authors pointed out the key challenges that these tools must address, which included ecological, economic, and social benefits derived by IS implementation to manufacturing sites while maintaining data confidentiality simultaneously.

5.2. Approaches and Platforms to Foster Urban IS

Understanding the influence of IS on the UM is quite a complex process, given the intricacies involved in this mutual synergy. There are concrete fields in which the urban sphere could actively promote the formation of symbiotic exchanges. To this purpose, the establishment of smart integrated matching platforms and related tools is increasingly advocated in the literature that can help grasp the complexity of urban metabolic streams and address the implementation of IS/UrS.\[122\] Furthermore, there is also the need for a simultaneous assessment of the environmental, economic, and social effects derived from such a symbiotic relationship.\[123,124\] While the implementation of such symbiosis is sometimes hindered by financial and infrastructural constraints, the existing urban infrastructure if carefully planned and managed could be facilitated to overcome these challenges and propel the push toward smart manufacturing, finally contributing to smart cities.

Fraccascia\[125\] analyzed the effect of online platforms on the emergence of IS relationships, utilizing an agent-based modeling approach, and concluded that exceeding a certain participant threshold has a significant effect on the individual network.
participants. Lu et al.\cite{111} developed an analytical model to evaluate the economic and ecological effects of urban IS on the metabolism of a city. They studied the symbiotic performance analysis in the city of Yongcheng in China and identified major consumers and waste producers in the urban environment. Significant saving potentials were identified with respect to waste recycling, raw material savings, and energy savings, and an outlook toward the enhancement of the approach by including LCA and social network analysis was recommended. Bin et al.\cite{114} explored the potential of big-data analytics for waste-to-resource mapping.

Using data mining approaches, manufacturing processes in an urban entity were identified. These data were used to create a correlation matrix to represent the input and output flows associated with the manufacturing process. Using the financial data (indirect method), the quantity of emitted resources was roughly estimated and approximated. In a related study, Tseng et al.\cite{126} identified a research gap that existed in the application of the big-data approach to foster industrial UrS.

In a semantic approach proposed by Trokanas et al.\cite{127} the potential participants of the resource exchange network within the IS domain were listed and detailed. Specific roles were assigned to each participant, whereby a participant could act either as a provider or as a consumer of resources. A participant could also serve as a solution provider, if they had the technology capability of material or energy conversions. Related semantic approaches to analyze and classify different types of resources are well reported in literature.\cite{128-131} These approaches greatly aid in the process to identify potential substitute resources not only of the alternative types but also with similar ones.

Raabe et al.\cite{132} proposed a system architecture of a collaborative platform between a waste-to-resource matching engine and an IS simulation system. While the first subsystem would store all the valid options for exchange of resources among the entities in a focal urban system regardless of its economic viability, the latter subsystem was utilized for agent-based simulation to provide decision support in terms of evaluating the technical feasibility and economic viability of the corresponding waste-to-resource matches. However, while the combined system could analyze the economic outcomes of resource exchange, its functionality was limited as environmental impacts during resource exchange could not be assessed. Low et al.\cite{102} developed a trilayer collaborative platform to foster IS in urban environment. The first layer (data layer) comprised an information repository of manufacturing firms which were a part of the IS network, information about the wastes and resources. The second layer (logic layer) included the computation models and algorithms used to process the information from the data layer to calculate the technically feasible waste-to-resource exchanges. The final layer consisted of a user interface (UI) which allowed users to interact on the platform, provide input of their own data, and evaluate the respective findings. A further contribution to this platform was made by Yeo et al.\cite{113} by incorporating the natural language-processing pipeline in the computational layer, which was designed to screen and scrape for online literatures and databases pertaining to data points and technologies for waste-to-resource conversions and automatically extract, add, and organize them to the existing repository. By integrating an IS–LCA engine in the logic layer, Kerdlap et al.\cite{114} enabled the environmental performance assessment on the very same platform at the IS network as well as at a single-point resource level.

5.3. UM-Based Approaches

Dijst et al.\cite{112} analyzed the various perspectives of UM and emphasized the importance of social and economic subsystems and their respective impacts on the flow of energy, water, and material. They proposed an UM framework correlating five elements of the UM including 1) flow and stock of materials, 2) activities that create or impact the flow or stock of materials, 3) needs from which the activities stem up from, 4) facilitators and constraints upon which the activities are dependent on, and 5) drivers that ultimately influence and drive the needs, activities, as well as flows and stocks. Wang et al.\cite{115} combined the material flows and stock analysis (MFSA) along with the geographic information systems (GIS) to develop a 4D GIS model to analyze the spatiotemporal and material metabolism evolution of buildings. The study primarily focused on the UM of construction-based materials and the model developed recommended the increased recycling of construction debris to reduce the consumption of fresh raw materials and also forecasted the landfill demands and its optimal locations. García-Guaita et al.\cite{133} integrated the material flow analysis (MFA) and LCA to identify main contributors of environmental impacts in an urban system. This unified approach could account for environmental impacts with an acceptable degree of confidence even in the case of limited or sparse data. The study also concluded that, by integrating social and demographic attributes, strategic urban planning and decision-making could be improved. Kennedy et al.\cite{99} provided a comprehensive set of indicators for analyzing the UM in megacities and claimed that the setting of limits for these indicators was a central challenge to standardize UM analysis and for the intercity comparison of UM.

UM tools were extensively reviewed by Mostafavi et al.\cite{136} whereby an integrated UM tool (IUMAT) was developed. The descriptive details of the implemented algorithms and the holistic structure of the IUMAT were also presented by Mostafavi et al.\cite{137} Applications of this very same tool for energy consumption as well as water consumption modeling were outlined and described in following studies.\cite{138,139} Respectively. Li and Kwan\cite{140} proposed a 3D geovisualization to eliminate the shortcomings of the existing UM analysis methods. This methodology could account for complex spatiotemporal characteristics of the urban system’s entities as well as its resource flows. The authors claim that GIS and visualization can play a vital role in boosting the tangibility and explicitly of the results derived from UM studies, which in turn could be translated into urban policies or suggestions. Basu et al.\cite{141} introduced a conceptual framework to map the complex urban energy systems in its entirety. The multilayered framework considers hierarchical dependencies and interlinkages along with the mapping of embedded social and contextual entities within the arger urban system. The proposed multilayered framework could allow for disaggregated as well as modular analysis of UM. Triantafyllidis et al.\cite{142} developed the platform named as resilience.io to evaluate urban infrastructural projects. In this twofold study, agent-based
models were first devised to model the dynamic population behaviors and obtain the estimated demand of resources, followed by mixed-integer programming to determine the optimal investment and operating solutions, accounting for both economic cost and environmental metrics such as GHG emissions.\textsuperscript{[143,144]} Figure 4 shows a pictorial representation of the review content presented in this section.

The increasing implementation of digital technologies (CPS) and the related increasing data availability in smart cities as well as smart manufacturing can be a promising catalyst for fostering IS in the urban space. The interface between the UM and IS platforms can enable improved data-based services and business models for fostering/incentivizing IS. For example, new business models based on intelligent networking offer the opportunity for the digital transformation of business processes toward a platform-based targeted exchange of information on the dynamic adaptation of available resource flows between the actors of a UrS/IS network. Therefore, resource flows within a UrS/IS network can be dynamically controlled based on available live data and according to the necessities resulting from city and/or industrial requirements, therewith providing the basis for new business approaches.

5.4. Section Summary and Key Challenges

A well-organized IS/UrS should be complacent to rigorous urban planning, whereby several factors such as urban density, centrality, and compactness in location and the degree of distribution and connectivity between the manufacturing industries and urban municipal communities are duly taken care of. The benefits derived through IS/UrS serve as a lever for not only smart manufacturing practices but also urban cities and municipalities, so that they can plan and encourage the creation and development of such synergies. In prospects within the IS/UrS framework, the tools and practices, which enable the quantification and matching of resource supply, efficient utilization through ease of distributions, and proximity of the manufacturing sites within the urban area, are enablers to the “urban planning” indicator of a smart city, whereas the successful implementation of these IS/UrS networks justifies and contributes to the “environmental” dimension of a smart city.

Despite the recognized economic and ecological benefits of IS/UrS, a number of challenges do exist that limit its acceptance and application at a large scale. The lack of stringent regulations, such as low taxes\textsuperscript{[111]} on landfill disposal or bare minimum penalty on GHG emissions,\textsuperscript{[145]} does not pose significant concerns to manufacturing companies and more often favour the aforementioned existing practices as compared with the establishment of IS/UrS networks. Another consideration from a cost-benefit perspective arises, wherein, the price for waste resource that consumer companies are willing to pay may not be economically beneficial for the waste producer company.\textsuperscript{[146]} In such cases there is a lack of incentive for companies to divert waste from landfills and start a symbiotic network. Needless to mention, the infrastructural cost required to establish such an IS/UrS network is an important consideration as well. Moreover, the reluctance of manufacturing companies to share relevant process data or data on waste generation, among themselves as well as with municipal corporations, is a major bottleneck in the establishment of such synergistic relationships.\textsuperscript{[102,116]} The volatile nature of the resource supply chain, within an IS/UrS framework, also increases the uncertainty in productivity and profit and has been identified as a barrier to such symbiotic relationships.\textsuperscript{[146]}

To this cause, some of the aforementioned challenges such as lack of trust for data sharing and a continued database of resource tracking to reduce volatility can be achieved by adopting open-end digital platforms among the collaborators\textsuperscript{[102,133]} interested in developing such symbiotic networks. Such digital platforms for material or energy exchange could offer a dedicated, resource-targeted, and resilient plan of action for the participating companies. The role of facilitators such as municipalities and industry associations is paramount, in driving the creation of trust and cooperation and helping to identify new symbiotic relationships.\textsuperscript{[147,148]} Lastly, legislations and policies that are consistent and strictly penalize emissions and disposal of waste\textsuperscript{[117,145]} can also encourage the formation of IS/UrS.

![Figure 4](https://www.advancedsciencenews.com)  
**Figure 4.** Overview of the industrial symbiosis section undertaken in this study. The order of the references represents the chronology in which they appear in the manuscript from first to last. The letters A, B, and C represent if the respective work involved case studies (A), and/or methodological approaches developed (B), and/or platforms implemented (C). Furthermore, the frame of reference is classified into industrial symbiosis, industrial/UrS, and UM represented by green tiles, whereas the orange tiles represent the mode of resource transfer, termed matchmaking. For example, the left-most column of tiles in the figure cites a previous study\textsuperscript{[107]} and has letter C. This indicates the research work\textsuperscript{[107]} focused on platforms implemented (C) for active transfer of resources (orange tile) in an IS (green tile) and IS/UrS (green tile) network. Similarly, the column of tiles to the immediate right cites a previous study\textsuperscript{[102]} and letter A. This means that the previous article\textsuperscript{[102]} presented an overview of industrial symbiosis (green tile) with a specific case study (A).
6. Singapore: A Smart Nation and Smart Manufacturing Hub

6.1. Government Initiatives

The constant evolution and long-term success of any smart city heavily rely on the contribution and support from the national and municipal governments. The role of government at both the national and the local level is undeniable in the transformational journey of a smart city, and some of the major contributions, among many others, include\(^{149,150}\) 1) support and advocacy of research and demonstration projects that develop and test particular new smart city applications; 2) allocation of national funds and investments targeted for smart infrastructure development and implementation; 3) development of policies and regulations for smart city technologies that allows new business models and disruptive entries, while simultaneously protecting the interests of citizens; 4) efforts to support smart cities, such as through pilot programs, infrastructure investment, or support for public-private partnerships; and 5) fostering collaboration and coordination in the smart city ecosystem to facilitate learning and reduce knowledge sharing barriers. To give a more precise understanding on this context, this section discusses and highlights the role of governments as enablers of a smart city, by taking Singapore as an example, which is both a leading smart nation and a technologically advanced manufacturing hub.

Driven by rapid economic growth, as well as being a promising market in terms of trade and finance, Singapore witnessed unprecedented urbanization in the last two decades. This placed substantial strain on the country’s resources, infrastructure, and quality of living in general. To meet these challenges and secure its growing urban economy, the government of Singapore introduced the “Smart Nation Program” by the end of 2014. The program aims to harness the state-of-art digital and disruptive technologies of AI, IoT, data analytics, and robotics and apply them to national challenges in five focus areas, including urban solution, transport, healthcare, education, and finance.\(^{151,152}\) Since its inception, the program has been quite successful in its endeavour to transform Singapore as a smart nation, evidenced by the consistency in the country’s global smart city ranking between 2017 and 2019\(^{11,12,15}\) and also seen in the earlier section of this Review.

Moreover, manufacturing has been a key driver of Singapore’s economy and accounts for one-fifth of its current GDP.\(^{16}\) Over the past three decades, Singapore has maintained a competent and reputable global standard in terms of manufacturing capabilities in the area of high-tech products, R&D, and product design. Given the importance of manufacturing in the country’s economy, the “Smart Nation Program” also emphasized on a strong framework to develop and drive Singapore’s future of manufacturing and production through the FoP initiative,\(^{153}\) where “Industry 4.0”-based platforms such as CPPS and technologies including IoT, AI, and data analytics were again identified as key enablers.

6.2. The Model Factory: Case Study

With reference to the FoP initiative, in this subsection, we present and discuss some of the recent initiatives and ongoing projects, which are implemented at SIMTech. We specifically focus on SIMTech’s Model Factory, a pilot-scale manufacturing environment with actual production capabilities, which also serves as a test bed to develop and deploy integrated and scalable CPPS modules and related decision support software/tools, specifically for the shop floor and supply chain network. The Model Factory also serves as a medium for existing manufacturing companies to learn, experiment, and co-create technologies essential for the futuristic smart factories. The following subsections highlight some of the important modules and submodules of the Model Factory, along with their intended application and implementation.

6.2.1. System Architecture

The system architecture for the Model Factory is shown in Figure 5, depicting the flow of data from the machines and field instruments to the dashboards on the client PC or mobile applications. The machine data are passed through the Edge PLC and subsequently distributed to the relevant apps via the MQTT broker system. Similarly, sharing of data between apps in the cyber environment takes place not only via the common database, but also, by the MQTT broker system for real-time transfer of data between the integrated physical systems and applications. This seamless exchange of production and supply chain data, along with their visualizations in real-time dashboards, is collectively catered via the Nerve Centre module of the Model Factory, which provides an overview of the entire production processes.

6.2.2. Module 1: Resource Management

The resource management module comprises two separate IoT-enabled software, called the smart energy management and smart waste management. Both these submodules allow for simultaneously the visualization and understanding of production data, its corresponding energy and resource consumption, and the potential to minimize or eliminate energy or resource wastages, via energy and waste benchmarking during the actual production process and in real time.\(^{154,155}\) Both the submodules make use of data envelopment analysis (DEA) to quantify and benchmark specific energy consumption (SEC) or waste generation intensity for a production process or at the machine level, respectively, in a production shop floor.

The DEA begins with the formulation of a linear programming (LP) model to minimize the SEC or waste generation for any given production process, depending on the respective submodules. The outcome of the LP model is expressed in terms of relative efficiency (\(\theta\)), which is further generalized using the quartile classification method. Within the quartile quantification, the performance of the production process in terms of SEC and waste generation performance is grouped into three classes: normal, warning, and abnormal, if \(\theta\) falls in third (Q3), second (Q2), and first (Q1) quartile respectively. Both the submodules are used as tools to visualize real-time energy and material wastage performance of a production process, on mobile devices and remote station with a network of sensors implemented at the
production station via Wi-Fi connection, thereby showcasing their IoT application as well.

6.2.3. Module 2: PdM in Shop Floor

PdM is one among a few other submodules of the shop floor main module. PdM encompasses a variety of functionalities, including root cause analysis (RCA), anomaly detection, and RuL, to monitor the health condition of the equipment on the shop floor. More specifically, the PdM module uses signal transformation methods such as the empirical mode decomposition (EMD) or wavelet transform (WT) to extract informative features from the nonlinear and nonstationary raw time-series signals. These transformed time-series features are then subjected to deep learning algorithms such as recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent units (GRUs), to determine the health condition and predict the RuL of the machines under consideration. The RCA of machine failure or breakdown is further identified based on a machine’s fault data stored in the database, which can be sourced via object linking and embedding for process control-United Architecture/MQTT protocols. These AI-based modules aid in the execution a cost-effective PdM program to minimize unplanned and unscheduled downtime.

6.2.4. Module 3: Supply Chain Logistics

The allocation and tracking submodule is a part of the supply chain logistics module and makes use of a genetic algorithm (GA)-based approach to allocate customized orders to various MTO production sites, via a two-step process. In the first step a greedy algorithm which decides the allocation order is devised, and a greedy index (GI) for each order is computed. The orders with the highest GI are shortlisted. In the second step, a cost function corresponding to either the transportation cost to the production side or its current loading capacity is developed. Subsequently, the shortlisted orders from the earlier step are allocated when the factory is least loaded or when the transportation cost to the production site is minimum. This second step is continuously optimized via the GA algorithm and is terminated when overall transportation costs and penalty costs for late deliveries are minimum.

7. Discussion and Future Directions

Value creation in the manufacturing industry has been a subject and witness to radical evolution over the past two centuries. Though industrialization has been a primer to urbanization, from a historical perspective, the two have never coexisted, primarily due to their nonconformities arising from negative industrial legacies to that of urban spatial constraints and residential lifestyles. As a result, manufacturing industries have mostly been located at the city outskirts. However, the futuristic manufacturing industry, given their ability to satisfy the indices of a smart city, could have new space in urban environments. This factor, in ways, would also justify the true essence of a smart city, where all its entities (including building, transportation, energy grids, healthcare, manufacturing, commercial services, etc.) are interlinked and leverage the benefits from each other. However, this integrated framework of a smart manufacturing unit(s) within smart cities will have to wait, as technical, social, and economic challenges do exist, that impede the large-scale implementation of smart manufacturing.

At the onset, it is worth a mention that scientific innovations and technological drive usually take about 4–5 decades to mature,
penetrate, and have widespread impact in any industry. For instance, the manufacturing assembly lines that sparked the second industrial revolution were first introduced in 1913 in the automobile industry, and it was not until the mid-1950s that mass production in manufacturing aided by assembly lines became a global phenomenon. Nearly a century later, the concept of “Industry 4.0,” the synonym to the fourth industrial revolution, was first introduced in 2011 and has promised a paradigm shift from production-oriented manufacturing to smart manufacturing. Though nearly a decade old, “Industry 4.0” is not a mature concept yet and might have a few more years or a decade at least to be the global norms.

Moreover, currently there exist a lack of a higher-end vision and understanding of smart manufacturing implementation at its benefits, at both the workforce and higher-management level. Least to mention, the inertia to move away from the old-generation production routines and the perceived threat to their established competencies cannot be neglected. Going forward, creating a more aware, educated, smarter, and technologically competent workforce as described earlier in this work can help address this point. Given its nascency, the complex nature of the technologies driving smart manufacturing is hard to comprehend, let alone gauge the potential benefits. This factor, coupled with the higher implementation costs, only exacerbates the uncertainty in the implementation of smart manufacturing technologies, as the return on investment cannot be easily quantified. Also, at an organizational level, barriers in migrating the traditional routines and processes which have been profitable over decades do exist and might delay the transformation journey toward smart manufacturing. Agile implementation processes including daily trials, short development cycles, and creating minimum viable solutions can aid in continuous and iterative evaluation cycles, which provide opportunities to adapt to these new smart manufacturing technologies and practices and eventually help build user confidence at various levels in any manufacturing organization.

Governments and national research agencies would also have to play an instrumental role, as their support in the form of seed funding or incentives along with economic policies that back the manufacturing industries to adopt the new technologies will only expedite the transformational journey. More so, a push toward a circular economy and sustainable practices through tax rebates while simultaneously incorporating emission taxes to curb industrial emissions and wastes would also be an active direction to be acted upon.

8. Conclusion

This Review collectively draws insights on the role and contributions of smart manufacturing within the framework of smart cities. Specific emphasis was laid on smart manufacturing practices that could serve as key enablers of a smart city by satisfying some of its key features such as digital technologies, smart citizens, government initiatives, environment, health and safety, and urban planning. In this context, the role of CPPS in the transition toward smart, decentralized, and automated manufacturing was first addressed, and the significance and application of ML in three main areas, process monitoring and control, PdM, and production, and supply chain planning, were expanded upon. This was followed by an understanding on the implications of automated and data-driven manufacturing from an ergonomic perspective and how it would contribute to greater job satisfaction to the workforce as well as improved safety conditions in a manufacturing environment. Further on, the fundamentals of IS/UrS in an UM, along with their methodical approaches, and the enabling platforms and tools were outlined. The importance of the IS/UrS framework from a circular economy perspective in smart manufacturing was emphasized and the overall contribution of IS/UrS networks in the grand scheme, value creation, and development of smart and sustainable cities was also described. Lastly, by taking Singapore as an example, the role of governments driving smart manufacturing initiatives was presented along with a brief overview of a smart manufacturing platform called the Model Factory that collectively summarizes the essence of this Review. On a concluding note, while the transitional journey toward smart and sustainable manufacturing has already begun, to be an integral part of a smart city, technical, social, and economic barriers do exist and these must be addressed, by giving due credits to each of these factors.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M.S. and X.W. conceived and executed the overall project. Review contents for Section 1–4 and 7, 8 were conceptualized and prepared by M.S. under the supervision of X.W. Review content for Section 6 was prepared by M.S. under the supervision of Y.T. L.B., J.H., and M.M. conceptualized and prepared the contents for Section 2, 5, and 7, supervised by C.H. L.J. contributed to Section 3. All authors discussed the review contents and commented on the manuscript.

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