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CIRCULAR ECONOMY INTER-CLUSTER KNOWLEDGE CREATION AND ORCHESTRATION USING INTERNET OF THINGS AND TRUST TECHNOLOGIES

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ABSTRACT

Techniques are described herein for an architectural model of a focused, integrated method for the use of collaborative, logistical, technologic, and commercial frameworks. These techniques are globally inclusive yet secure. This reduces barriers to participation while capturing and deducing relevant knowledge for continuous system improvement. The knowledge provides integral value to relevant individuals, groups, companies, and municipalities through an interconnection mechanism that spans geographies and industry verticals. This ability to create knowledge and then deliver it to the stakeholders in the Circular Economy (CE) may be a catalyst for new value creation.

DETAILED DESCRIPTION

One of the pillars of the Circular Economy (CE) often refers to an economic construct and value chain in which excess materials (waste) is collected and utilized in the production of new goods in support of existing value chains. This can occur either within the original value chain or in those of other industries. From this definition, it is possible to identify a major shortcoming of current CE initiatives.

This limitation, which severely impacts the realization of the CE potential in for-profit industries (particularly industry verticals with thin operating profit margins) is found in the basic interpretation of "economic systems." With current initiatives, CE is typically perceived as processes contained within the same plant or enterprise. While firms may consider multiple aspects of the process, they are generally looking at improvements in the supply chain and/or the waste management within their organizational boundaries (also known as "single-cluster CE"). This limited perspective fails to achieve the maximum efficiency for the specific industry or, more importantly, across industries. The single-cluster CE approach, while worthwhile, does not consider the opportunity associated with materials demands generated in multiple different processes from firms in other verticals. In these broader scenarios, the byproduct from one vertical may require less remanufacturing or preparation for use as a raw material in another vertical. This increases its value materially on both sides of the transaction. In other words, one industry's trash becomes another industry's treasure.

There are some existing examples showing the potential for CE processes working either within specific sectors (intra-cluster CE) or across sectors (inter-cluster CE). While these isolated opportunities are encouraging, a critical component is missing. There are no efficient ways to stimulate maximum efficiency and efficacy for CE across industries. The lack of an economically efficient, optimized model supporting intra-cluster CE-based commerce is a fundamental barrier to sustainable adoption of a closed-loop regenerative economic system. The process, architecture, and tools to enable this is provided as the inter-cluster CE model described herein.[1]

The nascent initiatives produced thus far attempting to improve residual/waste reuse are largely based on human-driven, communication-based actions. Given these inherent weaknesses, it is crucial to apply appropriate process and technology to create a sustainable model.

These problems are fundamental deficiencies not only in a common methodology, but also in mechanisms and a base platform capable of enforcing a high-efficiency CE model that facilitates interaction of multiple players across completely different verticals (e.g., oil and gas, food, packaging, chemical, municipalities, etc.). There is currently no mechanism to facilitate effective, efficient interactions, and nothing that enforces an automated, continually improving, self-learning inter-cluster CE. This is absolutely necessary to ensure sustainability and scale beyond aspirational or philanthropic motives.

A deeper analysis shows several contributing factors that inhibit effective inter-cluster CE. These factors include:

[1] Note that, in the description of this process, the use of waste to produce energy (e.g., incineration) is not considered to be an authentic CE process, despite its cross-cluster characteristic. This is due to its lack of true "circular" attributes which support the core tenant that CE shall offer benefits to every possible ring of the value chain.

1. Supply awareness, which relates to the lack of information regarding the availability of usable materials, processes, or other resources (e.g., industry A produces a specific quantity of waste X that is relevant to industry B for process Y).
2. Demand awareness, which relates to the lack of information or collaboration regarding potential uses for waste materials (e.g., industry A is unaware that their waste is valuable to the production cycle for industry B).
3. Methodology, which relates to the lack of standardized, managed processes to optimize overall resource utilization.
4. Platform, which relates to the lack of a smart, transactional platform to connect the relevant suppliers, buyers, materials processors, and transportation options for all players participating in the inter-cluster CE mechanism.
5. Orchestration, which relates to the lack of automated, intelligent oversight of the platform and data to generate a set of compounding network effects which can fully capture the knowledge and value of the inter-cluster CE model.

The inter-cluster CE orchestration engine may enable several use cases. The first use case involves the manufacturing industry. For example, in this use case, a textiles manufacturer advertises excess materials (scrap) from garment-making. An automotive manufacturer requires specific component materials for its new car upholstery. A materials processor is automatically discovered with the equipment and processes to repurpose the scrap material into useful materials for upholstery. Sensors in transportation trucks note available excess space to carry both the unprocessed and processed materials to desired locations. The orchestration engine automatically identifies the required participants and facilitates the connections to enable the transaction.

An example for the second use case involves the chemical industry. In this use case, sensors detect and communicate contamination with a batch of raw materials. Rather than sending the materials to waste (landfill or incineration), the orchestration engine discovers a “cleaning” processor with the ability to decontaminate.

The third use case example involves a smart city. In this use case, city waste management sensors alert that there is a large allotment of material within a truck shipment that was picked up. This information is automatically advertised. The orchestration engine infers that this material is a match to a manufacturer-posted need and makes the proper connection. It can also make a recommendation even if the demand has not been posted.

The fourth use case also involves the manufacturing industry. In this use case, a packaging manufacturer alerts that materials brought back in large quantities for recycling at a state's processing plant are not an exact match to their product and may be "counterfeit." Track/trace ensures relevant suppliers are tagged and alerted to provide remediation.

The fifth use case involves the food industry. In this use case, farms for wheat and other grains produce significant residual materials such as straw. Over time the orchestration engine learns many potential uses for straw and advertises to multiple industries to maximize value and minimize waste.

Solution

The techniques described below are designed to enable the automatic generation of connections between supply chain communities-of-interest that were previously unrelated, as well as the bottom-up, automatic generation of potential new transaction opportunities into a cross-industry marketplace based on internal identity of component materials. These techniques further enable granular visibility into all sub-components of a product providing the ability to automatically generate a marketplace for that component based on market parameters, and inclusion and collaboration of all participants in the value chain including materials processing and logistics providers.

To accomplish this, a knowledge base must first be established for capturing/storing information from subject matter experts and from automated systems, including the Internet of Things (IoT), about available materials including component parts/ingredients, novel uses, processes for processing, transportation options, regulatory requirements, etc. An adaptive machine learning approach is then used to discover, infer, and add new information to the knowledge base. For example, the system may learn from the human designers who are recommending new uses for the waste. The system constantly learns to provide the automatic creation of new options to augment/replace traditional supply chains. A trusted, secure, ledger-based transaction system may be used to enable instantaneous ownership transfer of materials and pull through the products lifecycle history from any product passport.

Methods must be established to enforce intra- and inter-cluster CE mechanisms for enterprises, firms, municipalities and other commercial activities. This facilitates access to new "green" resources in order to reduce costs and to comply with mandatory green economy initiatives in a simple, smart, and automated way. To meet this goal and help enable producer responsibility, domain and subject matter experts (e.g., supply chain owners, process planners, scientists, designers, etc.) are empowered to contribute relevant, trusted information about new sources for specific raw materials and resources needed for production processes. These new materials sources are derived from waste (e.g., takeback programs and the like) or other residual materials which are currently unknown and therefore unavailable to the buyer.

This is enabled through the creation of new industry cluster "dictionaries" and relative (or adaptive) intra- and inter-cluster semantics rules. The dictionaries and semantic rules together facilitate the optimized discussions (or transactions) that foster both independent transactions and sustained relationships between transactional parties.

These dictionaries are defined by Machine Learning (ML) algorithms applied to the most extensive application of knowledge mining within industry clusters (i.e., homogeneous verticals such as food, packaging, steel manufacturing, etc.). Semantic rules are defined by the application of ML algorithms to the most extensive application of knowledge mining both within and across clusters. "Discussions" are defined as short- or long-lived combinations of terms coming from dictionaries based on semantic rules and driven by optimization functions as described herein.

In one example, a tire manufacturing plant (Enterprise.A), which also recycles used tires, is assigned in the knowledge base to a tire manufacturing cluster (Industry.TM). A manufacturing company that makes various mats and floor coverings (Enterprise.B) is assigned to the floor covering manufacturing cluster (Industry.FCM).

Dictionaries are established for each of these entities. The tire manufacturing cluster's dictionary is referred to as D-TM, enterprise A's dictionary is referred to as D-EnterpriseA, the floor covering manufacturing cluster's dictionary is referred to as D-FCM, and enterprise B's dictionary is referred to as D-EnterpriseB.

The dictionary for the tire manufacturing industry (D-TM) contains a persistent statement (gathered from knowledge mining one or more sources such as scientific paper analysis, people interviews, web meeting analytics, industry documentation analytics, etc.) that declares that used tires contain 25% rubber on average.

The dictionary for Enterprise A (D-EnterpriseA) contains a transient statement (gathered from knowledge mining one or more sources from Enterprise A such as IoT sensors, Customer Relationship Management (CRM), etc.) that declares the Enterprise.A has ten tons of used tires in stock.

The dictionary for the floor covering manufacturing industry (D-FCM) contains a persistent statement (gathered from knowledge mining one or more sources such as scientific paper analysis, people interviews, web meeting analytics, industry documentation analytics, etc.) that declares that new outdoor mats for children contain 50% rubber.

The dictionary for Enterprise.B (D-EnterpriseB) contains a transient statement (gathered from knowledge mining of Enterprise.B such as IoT sensors, CRM, etc.) that declares that Enterprise.B has orders for four tons of children's mats.

Two of the persistent cross-cluster semantic rules (based on dynamic knowledge mining) are "Rubber from Industry.TM used tires can be used by Industry.FCM" and "Rubber from Industry.TM used tires can be reused within the same industry."

Using these transient and persistent rules, the orchestration engine can infer connections with measured degrees of confidence. These insights are referred to as "sentences." Sentences may also be transient or persistent. Combinations of sentences are referred to as "discussions."

In this example, a transient sentence automatically inferred by the optimization algorithm would be "Enterprise.B can purchase 2 tons of rubber from Enterprise.A." This sentence generates advertisements (messages) for each potential participant in the transaction, including relevant government regulations, potential transportation providers (with consideration for proximity and greenhouse gas emissions), and materials processing providers (to extract the rubber from the tires). Each of these intermediary organizations may also have dictionary references and semantic rules.

If a third enterprise (Enterprise.C) in the same cluster as Enterprise.A (D-TM) also has a demand for rubber, the discussion may be a combination of sentences such as "Enterprise.C can purchase up to X tons of rubber from Enterprise.A" and "Enterprise.B can purchase Y tons of rubber from Enterprise.A." Variables X and Y may automatically change as transactions occur.

The sentences, or discussions, may be transient (as in the aforementioned example) or persistent (e.g., indicating a stable and ongoing new supply chain). In either case, transactions may be stored in a blockchain to ensure traceability and non-repudiation.

The dictionaries, semantic rules, sentences, and discussions are constantly adapting using inputs from people and systems. This, together with the inference engine, allow the creation of a new, knowledge-based marketplace that includes new and ever-evolving types of supply chains.

Figure 1 below illustrates an example architectural overview.

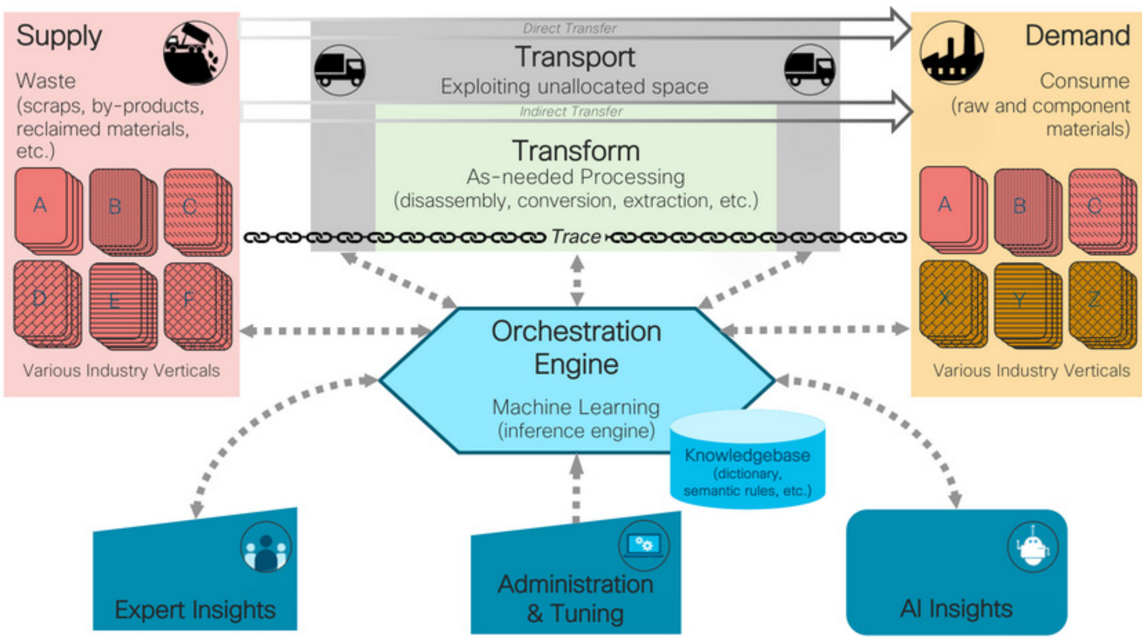

Figure 1

A platform may enable this by continuously learning and updating knowledge of all components within product clusters through machine learning and artificial intelligence (AI/ML) technologies. This would be constantly improving from both human interaction and AI/ML, and works with both intra- and inter-cluster CE opportunities. Moreover, the platform would include third-party materials processors and logistics providers to create extensions and efficiencies. The platform can be fully trusted due to the use of sophisticated tracking technology (e.g., blockchain), is accessible from various devices, mechanisms, and protocols, and provides a robust framework to complete transactions.

The methodology described herein operates in two steps connected in a self-improving loop. The first step is a knowledge discovery step to create the Intra- and Inter-Cluster Specific Descriptors (ICSD). This feeds the inter-cluster optimization phase (see below) to maximize the CE Resource Allocation (CERA). The second step is the knowledge discovery step which captures low-level, disaggregated data such as sensor data, expert opinions, warehouse management software data (via Application Programming Interfaces (APIs)), market data, and other relevant data.

Sensor data may be obtained from sensors used for tracking and tracing products or components for various purposes (e.g., location, condition, maintenance data, fatigue, custody (or chain of custody), etc.). Expert opinions may include all data related to material publicly available or through pre-defined prescriptions. Warehouse management software data may include Warehouse Management Systems (WMS) data available through business-to-business (B2B) interactions or through cloud/exchange services. Market data may include data relating to supply/demand, shortages, trading, geo-political factors, etc. Other relevant data may include data relating to weather, regulatory restrictions, traffic, etc.

This self-improving process results in "cluster-specific sets" which are collected at the firm/enterprise/municipality level to create a set of inter-cluster knowledge-based descriptors (e.g., users, resources, profit, and constraint/capability). These sets include descriptors of both intra-cluster domain-specific ontology (i.e., relevant within the same industry vertical cluster) and inter-cluster ontology (i.e., identifying relationships across different industry verticals). These ad-hoc, real-time intra- and inter-cluster descriptors are created to optimize the use of CE resources based on real-time input data.

In the inter-cluster optimization phase, previously calculated inter-cluster sets feed an optimization algorithm, referred to as the operation research knowledge base, to calculate the maximum total profit of resource consumption/utilization. This is based on previously calculated inter-cluster constraints/capabilities. The algorithm works on real-time data, gathering descriptors from the blockchain ledger (to assure reliability and accountability) and saving output in a blockchain distributed ledger as well.

The output of the algorithm provides both a) resource adoption models and transaction links for firms/enterprises/municipalities and b) knowledge input (ICSDs) for the next iteration of the knowledge discovery based on user feedback. Real-time knowledge-defined parameters may be used in the operations research optimization function and the output from that function may be used to contribute to the definition of a next-level iteration of parameters (continuous knowledge improvement).

Figure 2 below illustrates a high-level description of the overall system.

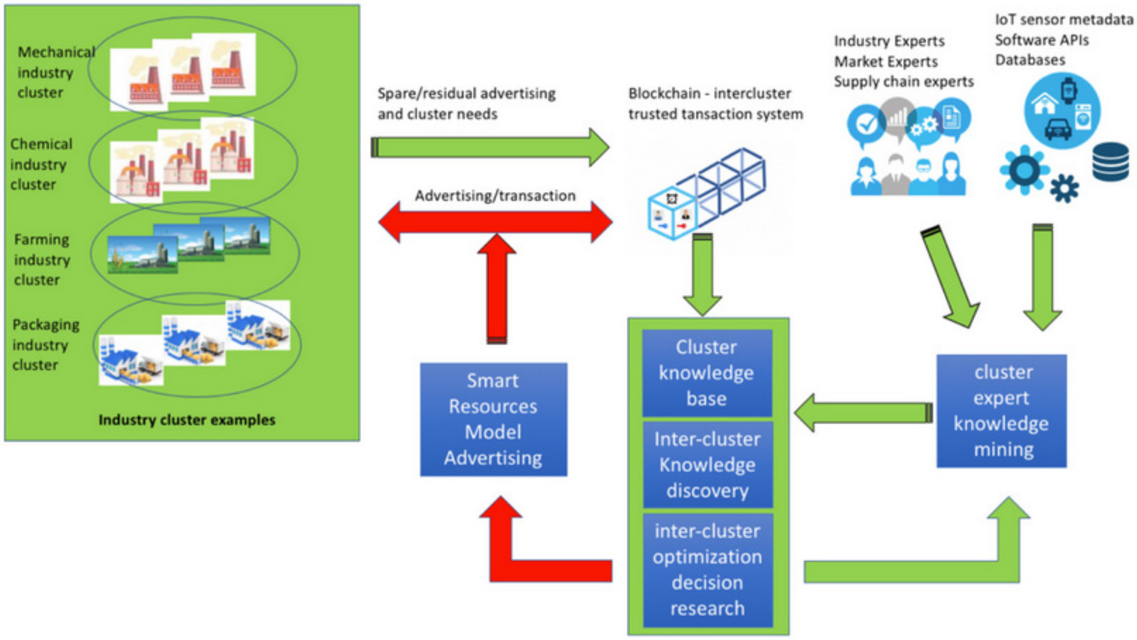

Figure 2

The cluster expert knowledge mining block illustrates how the orchestration engine uses cluster expert knowledge gathered and improved over time from industry subject matter experts to create intra- and inter-cluster datasets. Data may be collected from multiple sources, including social media, email, unified communication solutions, public interviews, online courses, direct interviews, scientific papers, etc. Relevant data (e.g., processes, needs, output, waste, residual, etc.) about specific processes may be collected and stored in a data lake using various knowledge extraction tools, including AI and semantic analysis. Human-defined input such as direct feedback and social input may be parsed to extract relevant knowledge by applying structured techniques for organizing and analyzing complex decisions. These techniques may be based on mathematics and psychology such as Analytic Hierarchy Process (AHP). Information collected from people may be anonymized and secured according to privacy regulations such as the General Data Protection Regulation (GDPR).

With respect to the cluster IoT sensor metadata mining block, similar to the human-based opinion mining, the orchestration engine also collects data from various technology-based sources to provide additional insights to validate the cluster expert knowledge mining. One such source may be IoT generated data (both sparse data from single sensors at the edge and aggregated data at higher levels of the network or in a data center). This approach leverages fog computing network hierarchy. Another technology-based source may be data generated from software systems such as Enterprise Resource Planning (ERP) systems to provide highly valuable information about manufacturing waste, raw materials, production capacity, and other relevant data. The orchestration engine may use AI algorithms as an inference engine to generate critical data (e.g., processes, needs, output, waste, residual, etc.) relevant to the processes and industries. Information collected from these systems may also be anonymized, secured, and managed according to privacy protection regulations such as GDPR.

With respect to the Inter-cluster Trusted Transaction System, depending on the size and scope of the system, this may be enabled with simple database and security models or through the use of distributed ledger technologies (e.g., blockchain). This component performs three functions: collection, reference, and transaction. For collection, it gathers and assembles information from industries and clusters about resources available for the CE process. Availability is maintained in a blockchain model to enforce traceability of goods. For reference, it stores the ICSDs since this represents the most updated knowledge available for the CE process. This is also used for continual analysis and improvement of CE models. For transaction, it serves as a secure transaction platform for enterprise/farm/municipalities when transacting the suggested CE trades. This means the block may become a crypto-currency solution for the CE-enabled exchanges and, at the same time, provide traceable information about the use of residual resources for optimization.

With respect to the cluster knowledge base, this component combines real-time information about resource availability with opinion mining to create real-time updates into the knowledge base to enhance both efficiency and effectiveness. This represents cluster specific knowledge. ML solutions may help build the relevant knowledge base. In other words, the application of ML algorithms applied to data gathered during the two aspects of cluster expert knowledge mining is used to produce the real-time descriptors about available cluster resources. Relevant descriptors feed an optimization function that amplifies the CE value within the same cluster applied in subsequent stages. This is an essential function of knowledge creation. If optimization functions (e.g., Multi-dimensional Knapsack Problem (MKP) algorithm) are used, then descriptors can assume values in the range. For instance, items, profits, resources, constraints and logistic weighted distances, market/geographical needs, etc. may all become applicable descriptors. MKP formalized the problem to select a subset of items (resource users) that will maximize the overall profit (specific value of a resource for an industry) of a specific set of resources (excess material) given some constraint/capacity (relevancy of material for a specific industry). In more general terms, MKP parameters may be considered a characterization of the cluster knowledge in terms of symbolic information, digestible from algorithms defined in the operations research theory.

With respect to inter-cluster (symbolic) knowledge discovery, this component is functionally equivalent to the cluster knowledge base but is differentiated by being designed to perform knowledge discovery for inter-cluster CE optimization. As described in the introduction, there is some knowledge today about intra-cluster CE models but almost no inter-cluster knowledge. In the aforementioned example, when using an MKP to solve the CE optimization problem, the inter-cluster knowledge descriptors may be similar to the definition of vector weights for variables in a MKP. This functional component may apply ML algorithms to the expert-mined knowledge regarding the relationships between clusters and the single-cluster knowledge bases to extract the inter-cluster knowledge base descriptors. The knowledge base extracted by this block is used for feedback to the cluster knowledge mining to contribute, in combination with the expert opinion mining, to building the next knowledge base iteration (refinement).

With respect to the inter-cluster optimization decision research block, this is the engine of the methodology described herein. It is designed to solve for optimal effectiveness and efficiency regarding the function F(x) of cross-cluster resource usage, based on the input coming from the cluster knowledge base (e.g., resources and cluster-specific constraints), and inter-cluster knowledge analysis (e.g., inter-cluster resources, profit and constraint/capability). The output of this component is a real-time updated knowledge base that contains relevant relationships about the optimization efforts of an overall CE economy for all the participating firms/enterprises/cities. There are known mathematical methods to achieve target function optimization. For example, one that could be considered is the MKP problem. The definition and solution of the problem cannot exist without a well-defined set of inputs that includes both cluster-specific and inter-cluster data (items, profits, resources, and constraints). The knowledge base extracted by this component is also used for feedback to the cluster knowledge mining to contribute, in combination with the expert opinion mining, to building the next knowledge base iteration (refinement).

The smart resource model advertising component performs two functions. The first function is exporting CE optimization orchestration models, relations, and values to the relevant industry clusters. This function may be performed "in-band," leveraging the Information-Centric Distribution (ICN) networking framework for descriptors distribution, resource notification and consumption (CE models advertisement) as part of discovery and transaction opportunities to industry clusters. The second function is to save the knowledge base and calculated optimal CE orchestration models into the blockchain block to ensure traceability of the overall CE process, as well as to enable a knowledge/participation base rewards mechanism.

In summary, CE describes an economic construct and value chain designed for regeneration. This model counters the traditional "take, make, waste" approach of the linear economy. Excess materials such as byproducts of manufacturing or residual materials at a product's end-of-life are used not as waste but rather as potentially renewable or reusable. Indeed, enterprises and governments are embracing this approach. In many countries, governmental regulations now include guidance on remanufacturing, repair, reuse, upgrades, recycling, recovery, proportioning of reused components and recycled contents, and the use of critical raw materials. Producer responsibility after the product is consumed is being added to laws in multiple countries.

Current efforts to create a CE cannot provide the ability to execute at scale and long-term economic viability, especially in a way that performs across both international and industry boundaries. This requires a comprehensive approach using new value chains that are collaborative, trusted, networked, automated, and "smart." Public and private sector entities are currently unable to do this due, in part, to an inability to capture adequate levels of expert knowledge such as raw material demand, materials supply, storage capacity, transportation options, and conversion processing capabilities. Moreover, resources are running out, which will drive the need for this orchestration.

In summary, the techniques described herein are for an architectural model of a focused, integrated method for the use of collaborative, logistical, technologic, and commercial frameworks to address this problem. This reduces barriers to participation while capturing and deducing relevant knowledge for continuous system improvement. The knowledge provides integral value to relevant individuals, groups, companies, and municipalities through an interconnection mechanism that spans geographies and industry verticals. This ability to create knowledge and then deliver it to the stakeholders in the CE may be a catalyst for new value creation.