Title
Mapping Opportunities for Transportation Electrification to Address Social Marginalization and Air Pollution Challenges in Greater Mexico City

Journal
Environmental Science and Technology, 54(4)

ISSN
0013-936X

Authors
Mahady, James Adam
Octaviano, Claudia
Bolaños, Oscar Sebastian Araiza
et al.

Publication Date
2020-02-18

DOI
10.1021/acs.est.9b06148

Peer reviewed

Renewable Energy 148 (2020) 1174–1189

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Design of domestic photovoltaics manufacturing systems under global constraints and uncertainty

José Ezequiel Santibañez-Aguilar [a, *], Sergio Castellanos [b, c, **], Antonio Flores-Tlacuahuac [a], Benjamin B. Shapiro [f], Douglas M. Powell [g], Tonio Buonassisi [d], Daniel M. Kammen [b, e]

[a] School of Engineering and Science, Tecnologico de Monterrey, Av. Eugenio Garza Sada 2501, Monterrey, 64849, Mexico
[b] Energy and Resources Group and Berkeley Energy and Climate Institute, University of California, Berkeley, 94708, USA
[c] California Institute for Energy & Environment, University of California, Berkeley, 94708, USA
[d] Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA, 02139, USA
[e] Goldman School of Public Policy, University of California, Berkeley, CA, 94708, USA
[f] E3 Consulting, USA
[g] Independent Consultant, USA

ARTICLE INFO

Article history:
Received 13 June 2019
Received in revised form
4 September 2019
Accepted 4 October 2019
Available online 9 October 2019

Keywords:
Multi-objective optimization
Solar photovoltaics
Manufacturing photovoltaics system
Expected value
Worst case
Uncertainty

ABSTRACT

As global political discourse is taking place where the need for a cleaner energy mix is constantly highlighted, manufacturing strategies are becoming more relevant. Thus, the photovoltaics system design is a crucial aspect related with the overall sustainability. In fact, various countries are considering the potential to locally manufacture different elements of the photovoltaics (PV) value chain and the strategies to incentivize a local manufacturing base. This paper develops a mathematical programming approach for the optimal design of a PV manufacturing value chain considering diverse criteria linked to economic and environmental performance such as minimum sustainable price, transportation capacity, among others, and considering uncertainty. In addition, the proposed methodology involves the dependence over time of supply chain variables and economic parameters such as inflation, electricity cost, and weighted average cost of capital, to determine the manufacturing system topology under uncertain conditions. Our results highlight the importance of planning models to develop markets policies related to supply chains, production level changes and imposed tariffs all while involving uncertainty in economic parameters, which is an improvement compared to planning models that use deterministic formulations. Finally, the proposed methodology and results can encourage decision-making considering probable variations in different parameters.

1. Introduction

The deployment of renewable energy technologies has increased in last decades across the globe. Specifically, photovoltaic (PV) generation technologies have become one of the most popular renewable electricity generation systems [2,3]. The dramatic cost reduction has been attributed in great measure to the expansion of manufacturing capabilities in countries with strong financial support [9].

In the foreseeable future, the growth of solar PV is expected to continue as multiple nations engage in decarbonizing strategies —which rely in renewable energy— to mitigate climate change [10–12].

To achieve decarbonized economies, an increase in solar PV manufacturing capacities across the world is required to ensure the achievement of terawatt (TW) levels of production[14]. This way, manufacturing costs play a crucial role in the design of supply chains and the study of them from a multinational perspective has gained importance.

Several works have addressed the PV manufacturing systems design to propose sustainable approaches to satisfy the increased

* Corresponding author. School of Engineering and Science, Tecnologico de Monterrey, Av. Eugenio Garza Sada 2501, Monterrey, 64849, Mexico.
** Corresponding author. Energy and Resources Group and Berkeley Energy and Climate Institute, University of California, Berkeley, 94708, USA.
E-mail addresses: santibanez.ezequiel@tec.mx (J.E. Santibañez-Aguilar), sergioc@berkeley.edu (S. Castellanos).

https://doi.org/10.1016/j.renene.2019.10.010
0960-1481/

demand for PV production while considering the impact of different cell and module components as well as economic variables. Ref. [13] used a bottom-up cost model to assess the impact of initial factory capital expenditure (capex) and minimum sustainable price (MSP) for a given PV manufacturing system. To compute the MSP they equated the weighted average cost of capital (WACC) with the internal rate of return, adjusting cash flows for various segments of the PV value chain.

Using the same techno-economic approach, Ref. [14] showed that a capital intensity reduction could effectively reduce the manufacturing cost and increase the production capacity. Ref. [8] examined the jobs and total economic impact of different PV system under diverse production capacity, and Kim and Jeong, (2016) developed two models to evaluate supply chain planning and choose recycling policies under several circumstances. However, most of these approaches do not incorporate the interactions between different countries that would better reflect globalized conditions. Furthermore, international trade conditions may be subject to tariffs by some countries to protect some small or local industries.

Recently Ref. [15], coupled the techno-economic tool developed by Ref. [9] with a transportation and tariff analytical framework to produce a strategy tool (TIT-4-TAT) to design PV manufacturing supply chains considering diverse value of tariff and transportation cost as well as different weighted objectives. Such approach, while useful, considers only deterministic cases, with single values for electricity, WACC, and inflation.

Supply chains are exposed to fluctuations of economic and technical parameters such as changes in input material costs, and product demand, which both can depend on global and domestic factors (see Refs. [16,17]). Because of these potential fluctuations, developing an uncertainty analysis is important to reach optimal and feasible planned solution, potentially unavailable through a deterministic approach under some situations the deterministic solutions could be sub-optimal or infeasible. In addition, a stochastic formulation could strengthen the basis for techno-economic model development with input parameters that include uncertainty during the solution procedure.

To address the uncertainty in PV supply chains, among other areas, Ref. [18], proposed an approach for the planning of a PV supply chain considering an analysis based on geographic information system (GIS) to determine potential manufacturing system locations considering uncertainty in the demand of annual solar energy through a set of scenarios. While this work accounts for interaction between different countries, it does not explicitly consider the imposed tariffs between them, which has been shown to strongly influence supply chain topology [15]. Furthermore, PV supply chain planning by Ref. [22] were designed considering uncertainties in individual parameters such as demand, and unit manufacturing cost (or unit inventory cost), excluding variations of economic factors such as inflation, which affect directly or indirectly all economic terms, nor WACC, or electricity.

In an attempt to address the aforementioned shortcomings, we herein present a tool for solar PV manufacturing supply chain design that considers multiple decision variables; which are taken into account in a composed objective function, akin to that developed by Ref. [15] and with the capability to incorporate and account for uncertainty in inflation, WACC, and electricity prices through a sampling method. Specifically, uncertainty is addressed via solving a stochastic formulation by maximizing the expected values of the composed objective.

Our model could be applied to evaluate and establish market policies to support a photovoltaic manufacturing supply chain development; starting from facility selection to decisions related to production capacity influenced by variations and uncertainty in inflation, cost of capital, and electricity price.

2. Problem statement

The most common procedure to manufacture a Si-based PV module requires the production of high purity silicon, casting it into ingots (if multicrystalline, or quasi-mono), wafering the ingots, before processing the wafers into solar cells, and assembling the cells into a module. All these processes compose a manufacturing system which is affected both by internal factors (*e.g.*, domestic fuel price, domestic production capacity, etc.) and external factors (*e.g.*, imposed tariff for different countries, petroleum price, labor cost, etc.).

Variations on economical parameters such as tariffs, inflation, electricity price, cost of capital, or other macro-variables could render significant changes in any supply chain. These changes might be production adjustment, closing of existing processing plants, or installation of new processing plants, which might not necessarily be the best solution.

This paper proposes a methodology based on mathematical programming for PV modules manufacturing supply chain design considering: (*i*) external factors, such as tariffs on exports and imports, (*ii*) uncertain values for inflation, electricity price and WACC, which are all subject to spatial and temporal variations, and (*iii*) internal factors characteristic of any manufacturing system such as transportation cost, manufacturing cost, and product and raw material prices.

Our proposed PV manufacturing analysis considers silicon extraction, ingot, wafer, solar cell, and PV modules production. Each manufacturing segment (silicon, ingots, wafers, cells and PV modules) considers the interaction between local and global markets through exports and imports.

The mathematical formulation can be textually stated as follows:

Given:

- Potential locations (internationally, or nationally) for manufacturing systems facilities
- Lower and upper bounds for expected range of electricity cost, inflation, and WACC
- Distance between potential manufacturing system nodes
- Transportation costs for final and intermediate products
- MSP dependence over processing capacity for each manufacturing stage
- Forecasted growth/demand projections for installed PV systems
- Potential import tariffs between different countries

Subject to:

- Input/output balance for each manufacturing step
- Limits for processing, demand, transportation, exports and imports in order to promote the local production
- Constraints to define if exports are permitted
- Equations to compute MSP

Determine:

- The optimal manufacturing system topology (*i.e.*, optimal selection for supply chain locations nodes), which can support the variations in addressed uncertain parameters.
- Production capacity value for the different selected processing nodes.
- Transported, exported and imported amounts for intermediate products and PV modules.

- Level of attainment for each of the considered decision variables.

It should be noted that manufacturing system topology is obtained by optimizing the expected value for different functions. In this way, simultaneous minimization of (*i*) MSP, (*ii*) exports, (*iii*) imports, (*iv*) transportation costs, and maximization of (*v*) local production is carried out via a composed objective function. For that reason, a stochastic problem should be formulated in order to obtain a solution including a set of values for inflation, WACC and electricity price.

3. Materials and methods

The approach herein presented considers several sequential stages in order to consider uncertainty in PV manufacturing system design under different decision criteria. The first stage is the scenarios generation for uncertain parameters, which are inflation, electricity price, and WACC. The second stage is the mathematical formulation considering the decision criteria such as transportation, exports, and imports costs. The third stage consists on solving the mathematical formulation for each decision criterion and the different scenarios to obtain upper and lower limits for the decision criteria. During stage four, we apply a stochastic multi-stakeholder approach based on the maximization of expected value of a composed function (where the composed function includes all decision criteria) and lastly, the PV manufacturing system topology is obtained. Fig. 1 depicts a general representation for the deployed methodology.

3.1. Scenarios generation

Zeroing in on the scenario generation, it should be noted that MSP can be strongly affected by variations in electricity cost, inflation, and WACC, since these factors are related to the operational cost and capital investment as well as the raw material price. Therefore, our methodology considers the generation of several scenarios where WACC, electricity price and inflation, are varied considering lower and upper bounds based on historical information, and own experience. Scenarios generation were carried out through Latin Hypercube Sampling considering a uniform distribution in order to generate a representative space for all uncertain parameters given the lack of specific probability density function for them. Additionally, each location has a different value for electricity price based on established limits which reflect historical ranges. We have not considered any correlation between uncertain parameters to avoid assuming a pre-established behavior between them.

3.2. Mathematical formulation

The addressed mathematical model is based on previous work presented by Ref. [15]. There are important differences and additional considerations contemplated in this contribution which are summarized in Table 1.

Additionally, other important aspects are discussed in detail in this section, where a semi-developed model is presented. The full model can be accessed in Supporting Information under the file MathematicalModel.pdf.

Prior to presenting the mathematical model, the main indexes, sets and notations for model are defined to help the model understanding. The definitions of main used symbols are shown as follows:

- *N* represents the sets for the supply chain facilities, hence, *N*0 is used for Polysilcon production nodes, *N*1 refers to Ingot producers, *N*2 corresponds wafer production nodes, *N*3 applies for cell producers, while *N*4 depicts the PV modules production nodes. It should be noted that all these sets are merged in index *j*; which considers elements in any of the *N*-sets.
- *S* corresponds to the used set for scenarios; whereas *s* represents an element in set *S*.
- *G* denotes the symbol used for material or good flow for the main elements in the manufacturing system, and the super index provides a brief description about which material is flowing.
- *MSP* is used to represent the minimum sustainable price (MSP) for a given supply chain node; it should be noticed that the super index and the sub index allows identifying which MSP is it being referred to.
- *TP* denotes the amount of transported product or by-products.
- *TC* denotes the transportation cost for the different goods in the manufacturing system.

3.2.1. Mass balances in domestic PV manufacturing system

Mass balances for supply chain nodes were done to determine the intermediate products (silicon, ingots, wafers, cells) and final product amounts (PV modules). Eq. (1) shows a generalization of the mass balances involved in each supply chain node.

$$G_{j,t,s}^{inventory} = G_{j,t-1,s}^{inventory} + \left(\begin{array}{c} \sum_{i \in PREVIOS} G_{i,j,t,s}^{intlet-local} + \sum_{ei \in EXPREVIOUS} G_{ei,j,t,s}^{import-international} \\ + G_{j,t,s}^{produced-local} - G_{j,t,s}^{toprocessing-local} \\ - \sum_{k \in NEXT} G_{j,k,t,s}^{outlet-local} - \sum_{ek \in EXTNEXT} G_{j,ek,t,s}^{export-international} \end{array} \right), \quad \forall s \in S, \quad \begin{array}{c} j \in \{N0, \\ N1 \\ N2 \\ N3 \\ N4\}, \\ t \in T \end{array} \tag{1}$$

Eq. (1) states that inventory level of any good (silicon, ingots, wafers, cells or PV modules) in the time t, $G_{j,t,s}^{inventory}$, is equal to the previous inventory level, $G_{j,t-1,s}^{inventory}$, plus the sum of goods from local production, $G_{i,j,t,s}^{intlet-local}$, plus the sum of goods from international production, $G_{ei,j,t,s}^{import-international}$, plus the amount generated or extracted in the supply chain node j, $G_{j,t,s}^{produced-local}$, minus the amount of processed goods (transformed in a different good), $G_{j,t,s}^{toprocessing-local}$, minus the amount of goods sent to the local manufacturing system, $G_{j,k,t,s}^{outlet-local}$, minus the amount of goods sent to the international market, $G_{j,ek,t,s}^{export-international}$.

It is worth noting that index j represents the supply chain node in which the balance is carried out. This index might be a processing stage focused on polysilicon, ingot, wafers, cells or PV

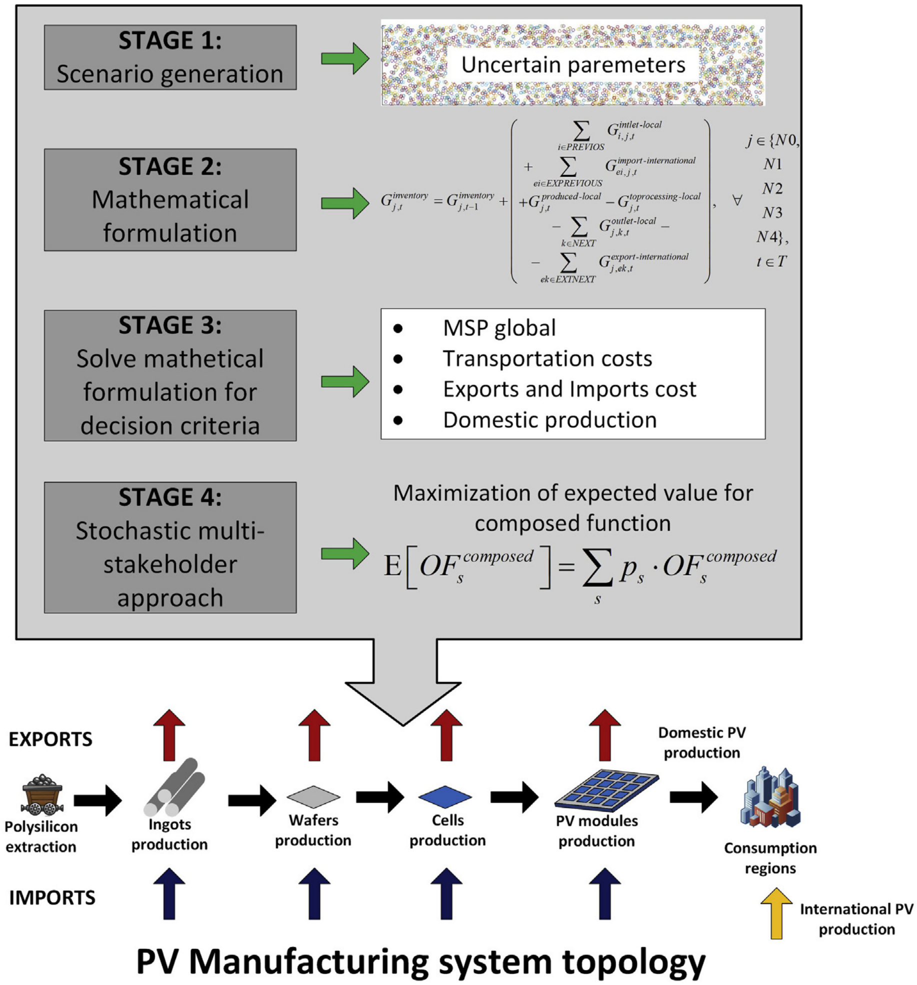

Fig. 1. Schematic representation of proposed supply chain and solution approach in this contribution.

Table 1
Differences of current work with that of [15].

[15]	Current work
• MSP dependence over processing capacity was considered through a decomposition of function into piecewise linear segments. • MSP dependence over processing capacity was based on a fixed value for electricity cost, WACC and inflation. • Global objective function was formulated as a composed function under certain parameters for each individual objective function.	• MSP dependence over processing capacity is adjusted to a non-linear and continuous function in order to provide a more realistic behavior. • Several MSP functions are obtained for different sets of values for electricity cost, inflation, and WACC. • A function for the expected value of the composed objective function is formulated considering the individual values for the composed objective function for each set of uncertain parameters.

modules production, where indexes i and ei represent the processing stage previous to stage j (i for domestic node, and ei for international node) as well indexes k and ek depict the next processing stage along the manufacturing supply chain. Table 2 summarizes the indexes and potential combinations of them constituting the formulation of Eq. (1).

Table 2
PV Manufacturing system nodes indicating their previous and next supply chain nodes.

Main node		Previous local node		Next local node		Previous external node		Next external node	
Index	Stage	Index	Stage	Index	Stage	Index	Stage	Index	Stage
n0	Silicon extraction	-	-	n1	Ingots production	-	-	e1	Ingots production
n1	Ingots production	n0	Silicon extraction	n2	Wafers production	e0	Silicon extraction	e2	Wafers production
n2	Wafers production	n1	Ingots production	n3	Cells production	e1	Ingots production	e3	Cells production
n3	Cells production	n2	Wafers production	n4	PV modules production	e2	Wafers production	e4	PV modules production
n4	PV modules production	n3	Cells production	n5	Market	e3	Cells production	-	-

3.2.2. Decision variables for PV manufacturing system

Decision variables are directly related with the PV manufacturing system configuration and they are stated as follows:

Global Minimum Sustainable Price.(MSP_s^{global}). It is a variable related to the product price when the net present value for productive processes is equal to zero [9]. Global minimum sustainable price, MSP_s^{global}, takes into account the MSP for each node in the manufacturing system, $MSP_{n0,s}^{Step0}$, $MSP_{n1,s}^{Step1}$, $MSP_{n2,s}^{Step2}$, $MSP_{n3,s}^{Step3}$, $MSP_{n4,s}^{Step4}$, as shown in Eq. (2). Global MSP considers only the terms with real contribution to the PV manufacturing system, such that, if a processing node is not used that processing node, it does not contribute to the global MSP.

$$MSP_s^{global} = \begin{array}{c} \sum_{n0} MSP_{n0,s}^{Step0} + \sum_{n1} MSP_{n1,s}^{Step1} + \sum_{n2} MSP_{n2,s}^{Step2} \\ + \sum_{n3} MSP_{n3,s}^{Step3} + \sum_{n4} MSP_{n4,s}^{Step4} \end{array}, \quad \forall s \in S \tag{2}$$

Transportation Cost to Markets.($TC_s^{Markets}$). At the end of the manufacturing system, the modules are shipped to consumer markets. These modules can be delivered from local or international manufacturing plants, therefore, global transportation cost to markets, $TC_s^{Markets}$, is equal to the transportation cost from local processing plants to markets, $TP_{n4,n5,s}^{local-PV} \cdot d_{n4,n5}^{local} \cdot TC_s^{local-markets}$, plus the transportation cost from international processing plants to markets, $TP_{e4,n5,s}^{international-PV} \cdot d_{e4,n5}^{international} \cdot TC_s^{international-markets}$. As shown in Eq. (3), transportation cost depends on the distance between PV-producer nodes (local and international), d, and end markets.

$$TC_s^{Markets} = \begin{array}{c} \sum_{n4}\sum_{n5} TP_{n4,n5,s}^{local-PV} \cdot d_{n4,n5}^{local} \cdot TC^{local-markets} \\ + \sum_{e4}\sum_{n5} TP_{e4,n5,s}^{international-PV} \cdot d_{e4,n5}^{international} \cdot TC^{international-markets} \end{array}, \forall s \in S \tag{3}$$

Local Production. (P_s^{Local}). Local manufacturing system can produce goods in each processing stage. Then, total local production, P_s^{Local}, considers mineral polysilicon, $P_s^{Local-Si}$, ingots, $P_s^{Local-ingot}$,wafers, $P_s^{Local-wafer}$, cells, $P_s^{Local-cells}$, and modules production, $P_s^{Local-PV}$, as shown in Eq. (4).

$$P_s^{Local} = \begin{array}{c} P_s^{Local-Si} + P_s^{Local-ingot} + P_s^{Local-wafer} \\ + P_s^{Local-cells} + P_s^{Local-PV} \end{array}, \forall s \in S \tag{4}$$

Exports Cost.($TC_s^{Exports}$). Exports cost, $TC_s^{Exports}$, accounts for the transportation cost by exporting materials (*e.g.,* ingots, silicon, wafers, or cells) as well as the paid tariff from the exported material and its amount, as denoted in Eq. (5).

$$TC_s^{Exports} = \begin{array}{c} \sum_{n0}\sum_{e1} TC_{n0,e1,s}^{Export-Si} + \sum_{n1}\sum_{e2} TC_{n1,e2,s}^{Export-ingot} \\ + \sum_{n2}\sum_{e3} TC_{n2,e3,s}^{Export-wafer} + \sum_{n3}\sum_{e4} TC_{n3,e4,s}^{Export-cells} \end{array}, \quad \forall s \in S \tag{5}$$

Imports Cost.($TC_s^{Imports}$). Imports cost, $TC_s^{Imports}$, sums the transportation cost by importing material (*e.g.,* ingots, silicon, wafers, or cells) as well as the paid tariff from the exported material and its amount, as stated in Eq. (6).

$$TC_s^{Imports} = \begin{array}{c} \sum_{e0}\sum_{n1} TC_{e0,n1,s}^{Imports-Si} + \sum_{e1}\sum_{n2} TC_{e1,n2,s}^{Imports-ingot} \\ + \sum_{e2}\sum_{n3} TC_{e2,n3,s}^{Imports-wafer} + \sum_{e3}\sum_{n4} TC_{e3,n4,s}^{Imports-cells} \end{array}, \quad \forall s \in S \tag{6}$$

Local Transportation Cost(TC_s^{Local}). Any manufacturing system has an associated transportation cost, which is directly related to the manufacturing system configuration because it considers the connections between all different nodes in production system. Eq. (7) states that the total local transportation cost, TC_s^{Local}, is equal to the sum of transportation cost between internal nodes, which consists on a unitary transportation cost, $TC_{n0,n1}^{Local-Si}$, $TC_{n1,n2}^{Local-ingot}$, $TC_{n2,n3}^{Local-wafer}$, $TC_{n3,n4}^{Local-cells}$, multiplied by the distance between involved nodes, $d1_{n0,n1}^{Local}$, $d2_{n1,n2}^{Local}$, $d3_{n2,n3}^{Local}$, $d4_{n3,n4}^{Local}$, and the amount of material transported, $TP_{n0,n1,s}^{Local-Si}$, $TP_{n1,n2,s}^{Local-ingot}$, $TP_{n2,n3,s}^{Local-wafer}$, $TP_{n3,n4,s}^{Local-cells}$.

$$TC_s^{Local} = \begin{array}{c} \sum_{n0}\sum_{n1} TP_{n0,n1,s}^{Local-Si} \cdot d1_{n0,n1}^{Local} \cdot TC_{n0,n1}^{Local-Si} \\ + \sum_{n1}\sum_{n2} TP_{n1,n2,s}^{Local-ingot} \cdot d2_{n1,n2}^{Local} \cdot TC_{n1,n2}^{Local-ingot} \\ + \sum_{n2}\sum_{n3} TP_{n2,n3,s}^{Local-wafer} \cdot d3_{n2,n3}^{Local} \cdot TC_{n2,n3}^{Local-wafer} \\ + \sum_{n3}\sum_{n4} TP_{n3,n4,s}^{Local-cells} \cdot d4_{n3,n4}^{Local} \cdot TC_{n3,n4}^{Local-cells} \end{array}, \quad \forall s \in S \tag{7}$$

3.2.3. Economic and technical constraints

Additional constraints are added to the mathematical model to consider important aspects such as the economic performance of

PV manufacturing systems. We utilize MSP as one of the most important variables to evaluate the performance of production system, as done in previous works [13,15].

Using the proposed model by Ref. [13]; a MSP value is computed for a base case of 400 MW, including inflation, electricity cost, and WACC. Subsequently, a MSP function over a range of processing capacity is obtained. It is worth noting that MSP as a function of processing capacity is a non-linear and a non-convex function. For that reason, these values are fit to a base function via the software ALAMO [23] and used then in a mathematical programming approach. In addition to extracting a base function, the electricity cost, WACC and inflation are incorporated as uncertain parameters, and are defined for each potential location in the manufacturing system.

3.3. Objective function and stochastic multi-stakeholder

Decision variables are introduced on each scenario as the formulation considers uncertainty for inflation, electricity price and WACC values on each iteration. If any of those values change, then the global MSP changes and by consequence the values for supply chain flow. Hence, a composed function ($OF_s^{composed}$) is formulated in order to optimize different issues simultaneously (see Eq. (8)). In this sense, the composed objective function considers a term per each of the aforementioned decision variables (Global Minimum Sustainable Price, Transportation Cost to Markets, Local Production, Export Costs, Import Costs and Local Transportation Cost), multiplied by a weighting factor. The weighting factors which are given for each decision variable are: ω_{MSP}, ω_{TCM}, ω_{LP}, ω_{TCE}, ω_{TCI}, ω_{LTC} respectively and they could be used by stakeholders to prioritize each decision variable (in a multi-stakeholder approach as seen in Refs. [29] and [24]; nevertheless, herein the decision variables have equal importance and therefore these factors are equal.

$$OF_s^{composed} = \begin{array}{l} +\omega_{MSP} \cdot \dfrac{{}^{Upper}MSP^{global} - MSP_s^{global}}{{}^{Upper}MSP^{global} - {}^{lower}MSP^{global}} \\ +\omega_{TCM} \cdot \dfrac{{}^{Upper}TC^{Markets} - TC_s^{Markets}}{{}^{Upper}TC^{Markets} - {}^{Lower}TC^{Markets}} \\ +\omega_{LP} \cdot \dfrac{P_s^{Local} - {}^{Lower}P^{Local}}{{}^{Upper}P^{Local} - {}^{Lower}P^{Local}} \\ +\omega_{TCE} \cdot \dfrac{{}^{Upper}TC^{Exports} - TC_s^{Exports}}{{}^{Upper}TC^{Exports} - {}^{Lower}TC^{Exports}} \\ +\omega_{TCI} \cdot \dfrac{{}^{Upper}TC^{Imports} - TC_s^{Imports}}{{}^{Upper}TC^{Imports} - {}^{lower}TC^{Imports}} \\ +\omega_{LTC} \cdot \dfrac{{}^{Upper}TC^{Local} - TC_s^{Local}}{{}^{Upper}TC^{Local} - {}^{Lower}TC^{Local}} \end{array} \quad \forall s \in S \tag{8}$$

Each aspect to be optimized is normalized in order to avoid biasing results. Each normalized term is equal to the difference between the value in that scenario and the target value, divided by the difference between the upper (${}^{Upper}MSP^{global}$, ${}^{Upper}TC^{Markets}$, ${}^{Upper}P^{Local}$, ${}^{Upper}TC^{Exports}$, ${}^{Upper}TC^{Imports}$, ${}^{Upper}TC^{Local}$) and lower limit (${}^{Lower}MSP^{global}$, ${}^{Lower}TC^{Markets}$, ${}^{Lower}P^{Local}$, ${}^{Lower}TC^{Exports}$, ${}^{Lower}TC^{Imports}$, ${}^{Lower}TC^{Local}$) values of that variable. The target for each aspect is different and they are stated as follows:

- **Domestic transportation cost.** (**TC_s^{Local}**). The target for the domestic transportation cost is the lowest possible, which could be zero, indicating that the domestic production would be zero, too.
- **Export and import costs.** (**$TC_s^{Exports}$** **and** **$TC_s^{Imports}$**). The target value for export and import costs should be the lowest possible if increased domestic production is sought. A global PV manufacturing supply chain, however, is subject to market price and sometimes exports and imports could be deemed necessary by some countries to protect certain industries.
- **Transportation cost to market.** (**$TC_s^{Markets}$**). To decrease the total cost of a PV manufacturing supply chain, transportation costs to consumption regions should be as low as possible.
- **Minimum Sustainable Price.** (**MSP_s^{global}**). The best MSP value from a consumer and a competitive manufacturer should be low, but if MSP is zero, there would be no domestic production.
- **Domestic production.** (**P_s^{Local}**). The best value for domestic production should be the highest possible if the promotion of local production is desired, although if the domestic production is large, then local production nodes could require external sources (imports) and sinks (exports).

Furthermore, Eq. (8) considers the values for upper and lower limits for each individual considered decision variable, where upper and lower values represent the best and the worst-case values, depending on the decision variable selected. It should be noticed that a high value for the compromise solution means that the decision variables are closer to the target, or its best value; where the maximum possible value for the compromise solution (Eq. (8)) is 1.

However, this work does not consider optimizing a single objective function as presented by Ref. [15] since the composed objective function ($OF_s^{composed}$) varies on each scenario given that values are changing on every iteration of the simulation run. For that reason, the expected value for the composed objective function ($E[OF_s^{composed}]$) is proposed as the objective function to be maximized (Eq. (9)).

$$E\left[OF_s^{composed}\right] = \sum_s p_s \cdot OF_s^{composed} \tag{9}$$

It is crucial to mention that Eq. (9) considers the combination of all possible values for the compromise solution shown in Eq. (8). Hence, the compromise solution in Eq. (8) depends on different scenarios for uncertain parameters. Even though each scenario could have different probability to occur, we considered equal probability for each scenario. Therefore, Eq (9) corresponds to the expected value of the compromise solution considering all scenarios with variations on electricity price, WACC and inflation. Consequently, if the expected value for the compromise solution is maximized, then the individual compromise solution for all scenarios is maximized, too; which means that the best values for decision variables in each scenario are being sought.

At this point, the amount of produced product, transportation costs, and global MSP, could be different in each scenario because these are operating variables. However, the location of manufacturing processing system nodes should not change with each scenario since in a realistic approach; the property, land, and equipment would be hard to relocate if WACC, electricity price or inflation values change, and these investment decisions are considered relatively inelastic once taken. Hence, the expected value for the objective function should be maximized to find the best manufacturing system topology overall, where the manufacturing system topology should be equal for all scenarios.

Eqs. (10–14) ensure that the supply chain topology is maintained. In this regard, the mathematical formulation includes binary variables associated to the selection of manufacturing system nodes for each scenario ($y_{n0,s}^{Local-Si}$, $y_{n1,s}^{Local-ingot}$, $y_{n2,s}^{Local-wafer}$, $y_{n3,s}^{Local-cells}$, $y_{n4,s}^{Local-PV}$), which should be equal to the corresponding binary variable linked to the existence of the supply chain nodes ($y0_{n0}^{Local-Si}$, $y1_{n1}^{Local-ingot}$, $y2_{n2}^{Local-wafer}$, $y3_{n3}^{Local-cells}$, $y4_{n4}^{Local-PV}$).

$$y_{n0,s}^{Local-Si} = y0_{n0}^{Local-Si}, \quad \forall n0 \in Producer^{Si}, s \in S \tag{10}$$

$$y_{n1,s}^{Local-ingot} = y1_{n1}^{Local-ingot}, \quad \forall n1 \in Producer^{ingot}, s \in S \tag{11}$$

$$y_{n2,s}^{Local-wafer} = y2_{n2}^{Local-wafer}, \quad \forall n2 \in Producer^{wafer}, s \in S \tag{12}$$

$$y_{n3,s}^{Local-cells} = y3_{n3}^{Local-cells}, \quad \forall n3 \in Producer^{cells}, s \in S \tag{13}$$

$$y_{n4,s}^{Local-PV} = y4_{n4}^{Local-PV}, \quad \forall n4 \in Producer^{PV}, s \in S \tag{14}$$

3.4. Solution approach

In order to obtain the optimal manufacturing system configuration, the optimization problem is undertaken via 3 steps:

1. Decision variables are maximized and minimized to get the upper and lower limits for each decision variable and scenario.
2. The maximum and minimum values for each decision variable and scenario are sorted to select the highest and lowest values for each one. This allows us to choose the worst and best case for decision variables.
3. The expected value of the composed objective function (Eq. (9)) is maximized to reach the target value for each decision variable and determine the final topology of the PV supply chain.

4. Case study

The proposed methodology was applied to a case study for the design of a manufacturing processing system for the PV modules production in Mexico, continuing on the previous work reported by Ref. [15]. Nine polysilicon producers that have reported possibility to extract polysilicon and other minerals (see Ref. [25]) are selected in the configuration. These polysilicon producers are located in states of Veracruz, Sonora, Chihuahua, Zacatecas, Nuevo Leon, San Luis Potosi, Guanajuato, Puebla and Michoacán. The maximum silicon production has been assumed as 25,000 metric tons/year.

As previously stated, PV manufacturing systems consist of locations where polysilicon is extracted and ingots, wafers, cells and PV modules are produced. In this context, our study case considers a producer per each state (32 total) for each manufacturing segment. The assumed locations of the manufacturing system nodes are the capitals of states. This assumption considers all processing nodes as a distributed system along the country.

In addition, it is worth noting that a key difficulty in any techno-economic model is establishing credible input parameters; which can be a disadvantage in a deterministic model. To address this drawback, we consider a set of values for inflation, electricity price and WACC between upper and lower boundaries based on conversations and own expertise; therefore, the obtained supply chain configuration will be based on different intervals for uncertain parameters and not for specific values.

Table 3
Upper and lower bounds for inflation, WACC and electricity price.

	Upper bound	Lower bound	Units
Inflation	0.07	0.02	-
WACC	0.16	0.08	%
Electricity price	0.20	0.02	$US/kWh

The uncertain parameters in this study (inflation, electricity price and WACC) were sampled using a Latin Hypercube Sampling method, and where inflation was modeled with the same value for all states on each scenario, while WACC and electricity price were considered different in each of the states, or nodes, every scenario. Table 3 reports the upper and lower bounds considered for the parameters with a range of possible values.

Additionally, this case study considers China as the only external supplier given its large manufacturing infrastructure for multiple products and energy, making it also the world's PV manufacturing leader for many years [3,9,26].

As for the end markets, or consumption regions, we consider 34 regions (32 Mexican states, USA, and Brazil).

The mathematical model considers different tariff levels between external suppliers and global markets. In this contribution we utilize on a scenario with high tariff levels between countries from Ref. [15]. Fig. 2 shows a schematic representation of the imposed tariffs among different countries. Given historical trends in multiple products, and to simplify the model solution, null tariffs are assumed for Mexico.

Furthermore, contemplating a desire to promote local production, the imported goods must contain less than 30% of the total and the remaining must be from local goods, and simultaneously the maximum amount to be exported is up to 90% of the local production.

5. Results

5.1. Scenarios generation and influence over MSP

Upper and lower boundary values were set for electricity price, inflation and WACC, and then random values were generated for each supply chain node, leading to N scenarios generated per node.

The cumulative probability for WACC, electricity price and inflation are shown in Fig. 3a, Fig. 3b and c, respectively, denoting a uniform distribution. These values are generated for each manufacturing node, which is assumed to be equal to each federal state.

As it can be observed, it is considered a uniform distribution for inflation, WACC and electricity price. Nevertheless, inflation is different in each scenario, but it has equal value for each node.

To illustrate the parameter space covered for this study, Fig. 4 shows the relationship between electricity price and WACC across all modeled scenarios. Fig. 4a illustrates the WACC dependence over electricity price considering only 1 scenario, while Fig. 4b shows the relation for only 10 scenarios. Fig. 4c depicts this behavior for 50 scenarios and Fig. 4d presents the relationship between WACC and electricity price considering 100 scenarios.

Fig. 4a shows that 1 scenario involves a large number of potential values of WACC and electricity price but not all their combinations. In contrast, Fig. 4d illustrates that almost full uncertain space is met with 100 scenarios; therefore, it is possible to see that most of combinations of WACC and electricity price are taken into account when 100 scenarios are considered and that 100 scenarios are appropriate to cover the uncertain space in this context.

Similarly, Figs. 1S–2S (Supplementary Material), show the relationships between WACC and electricity price regarding inflation, respectively. Fig. 1Sa and 2Sa show the case for 1 scenario, Fig. 1Sb

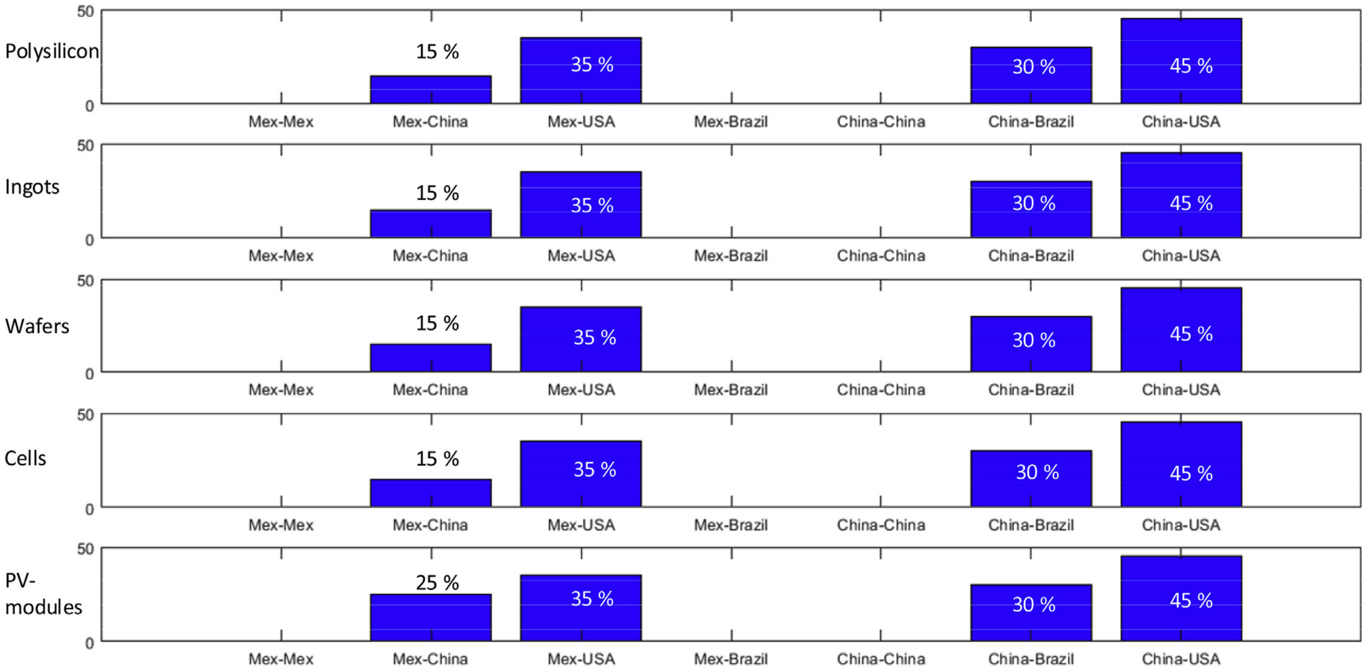

Fig. 2. Schematic representation for imposed tariff between different countries and type of good.

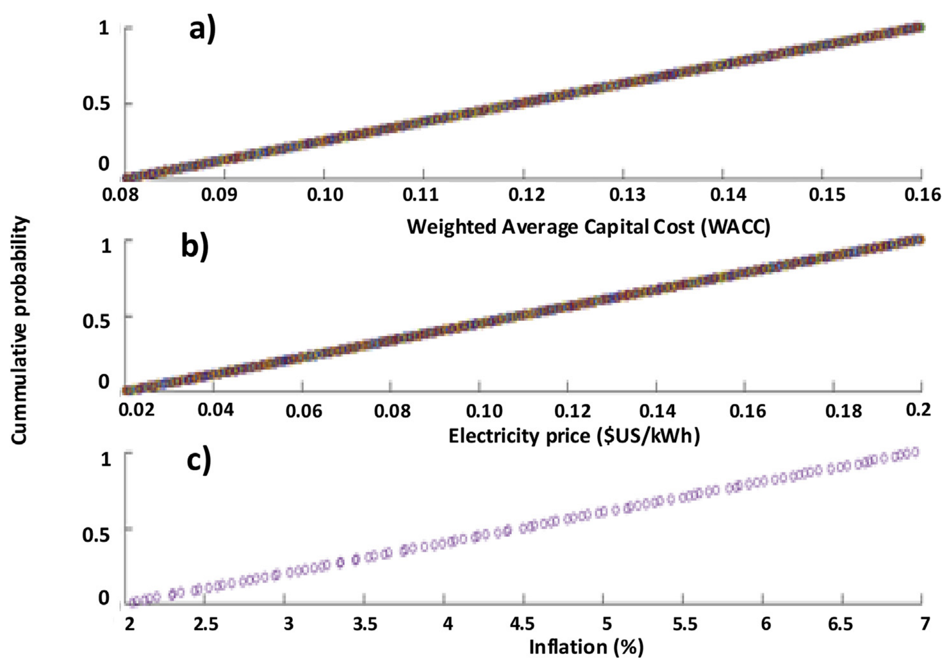

Fig. 3. Cumulative probability vs. values of uncertain parameters. a) WACC case, b) Electricity price case, c) Inflation case.

and 2Sb illustrate the case for 10 scenarios. Case for 50 scenarios are provided in Fig. 1Sc and 2Sc and finally, Fig. 1Sd and 1Sd depict the case for 100 scenarios. In general, Figs. 4, 1S and 2S show that uncertain space is almost fully met with 100 scenarios. In this regard, there might be high and low values for WACC and electricity price under different inflation values, and it is possible to observe different inflation values per scenario, but these are equal all manufacturing system nodes during each iteration.

Fig. 5 shows a statistical analysis for the MSP at 400 MW (reference capacity) through the method of standardized regression coefficient (SRC) (see Refs. [21,27] for each processing stage. This statistical method is useful to identify the contribution of a dependent variable, for example MSP, regarding different independent variables such as inflation, WACC and electricity price. Moreover, this statistical method allows to determine if independent variables has a direct effect on the dependent variable.

Fig. 5a presents the square of the standardized coefficients for the WACC electricity price and inflation, where it can be observed that electricity price is the uncertain parameter with major contribution to the MSP for most of processing stages; which is a

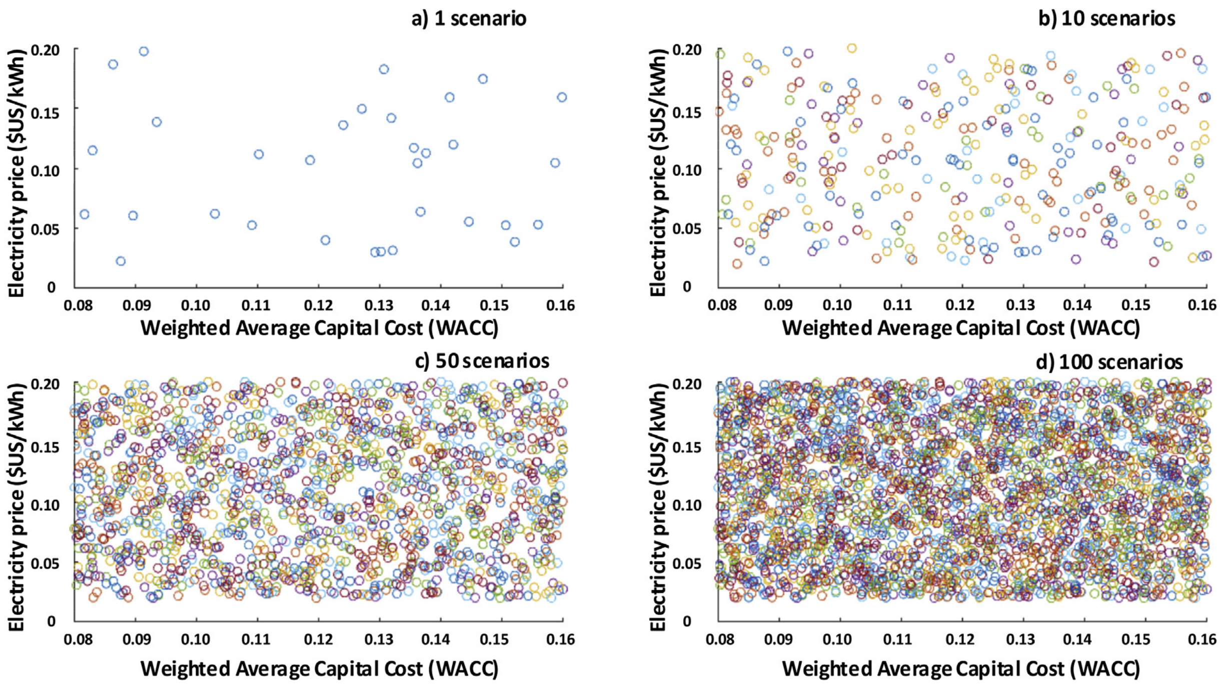

Fig. 4. Relationship between electricity price and WACC regarding different number of scenarios. a) Case for one scenario, b) Case for 10 scenarios. c) Case for 50 scenarios. d) Case for 100 scenarios.

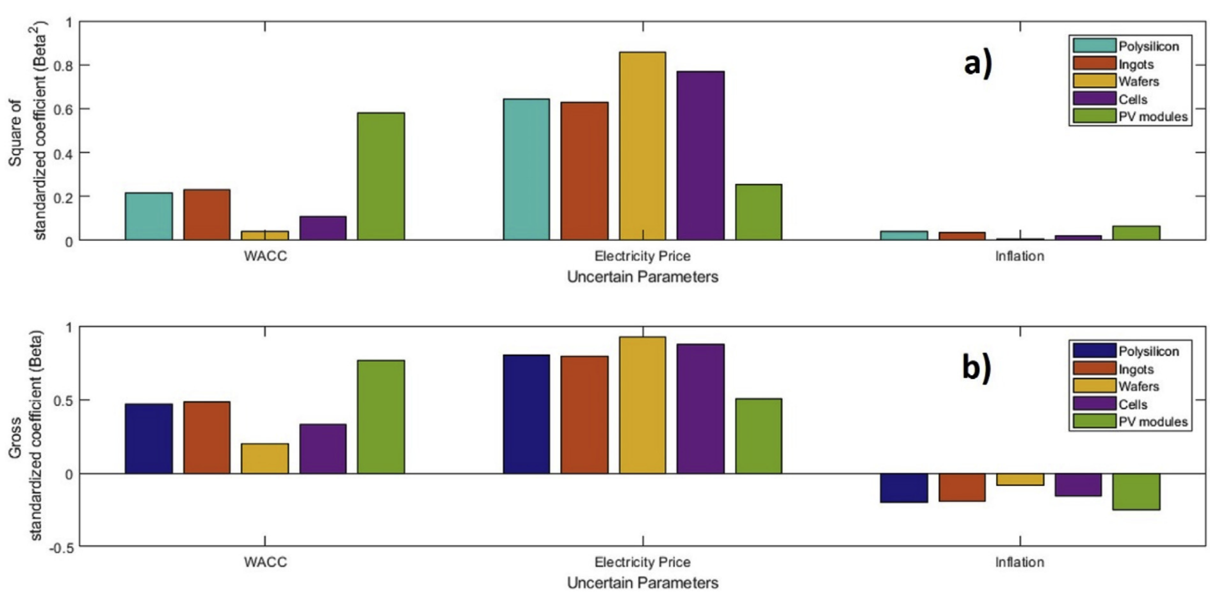

Fig. 5. Standardized Regression Coefficient Analysis for MSP at 400 MW under uncertain parameters. a) Square of standardized coefficient, b) Gross value of standardized coefficient.

Table 4
Correlation and determination coefficients from SRC for each processing stages based on uncertain parameters and MSP function.

	Polysilicon	Ingots	Wafers	Cells	PV modules
Correlation Coefficient (R)	0.9502	0.9500	0.9508	0.9506	0.9493
Determination Coefficient (R^2)	0.9029	0.9024	0.9040	0.9037	0.9012

significant contribution since this factor for electricity price is greater than 0.70. In contrast, the inflation is the parameter with the lowest contribution to the MSP function.

Fig. 5b depicts the standardized coefficients obtained from the statistical analysis. It can be observed that the contribution of inflation over the MSP is inversely proportional because the standardized coefficients for inflations are negative for all processing stages. Data for MSP, inflation, WACC and electricity price used for this statistical analysis are provided in data repository. Link for this repository is provided in Data Availability Section.

Regarding the contribution to MSP per each processing stage, Fig. 5a and b shows that wafer production is the most affected processing stage per electricity price, whereas the WACC value affects mainly the PV modules production.

In addition, Table 4 contains the values for correlation coefficients, R, and the determination coefficients R^2 obtained during the statistical analysis for each of processing stage. These values indicate a high correlation of the considered uncertain parameters with the MSP function.

Based on results from SRC method we can confirm that the changes in the assumed uncertain parameters have a direct impact in the value of MSP and consequently in the final supply chain topology.

5.2. Minimum sustainable price as production capacity function

As mentioned in previous sections, non-linearities exist for the MSP function vs. production capacity for each manufacturing node, constituting a challenge for solving the mathematical programming problem. The MSP values as a function of production capacity, given in Eq. (15), are restricted with lower and upper capacity limits of 20 MW, and 1975 MW, respectively, when processed through the ALAMO software. This limit assumption simplifies the function form because for a higher production capacity, the MSP become virtually constant, while for low capacities (lower than 20 MW) the MSP value increases exponentially. Coefficients and fit errors (ranging between 0.1 and 7%) for each manufacturing stage are calculated.

$$MSP_{node,s} = a_{node,s} \cdot CAP_{node} + b_{node,s} \cdot \ln(CAP_{node}) + c_{node,s} \cdot (CAP_{node})^2 + d_{node,s} \tag{15}$$

5.3. Optimal manufacturing system topology

It is worth noting that each decision variable was optimized separately in order to obtain the maximum and minimum values for each of the decision variables. The optimization procedure (*i.e.*, minimization or maximization) corresponds to maximizing and minimizing the variables calculated in Eqs. (2)–(7) subject to constraints (see Supplementary Material) for each set of uncertain parameters: inflation, WACC and electricity price. The 'worst case' and 'best case' categories shown in Table 5 are assigned to the minimum and maximum values obtained and the corresponding target value for each decision variable. Target values were previously defined in Decision variables for PV manufacturing system subsection. In this regard, Table 5 summarizes the worst and best values for the decision variables (see Eqs. (2)–(7)).

Table 5
Worst and best case for decision variables for the manufacturing processing system.

Decision Variable	Units	Worst case	Best case
Global Minimum Sustainable Price	\$US/W	9.0203	0.74
Transportation Cost to Markets	Millions \$US	411.5740	54.26
Local Production	Millions MW	0	1.2422
Exports Cost	Millions \$US	3.8630×10^3	0
Imports Cost	Millions \$US	6.7639×10^3	0
Local Transportation Cost	Millions \$US	372.9167	0

Maximum and minimum values for decision variables define the worst and best cases for each of them to be included in the composed objective function as upper and lower bounds (see Eq. (8)).

The worst and best values for decision variables are comparable with previous obtained limits for similar systems in previous work by Ref. [15]. For instance, the best obtained value in Ref. [15] for transportation cost to markets was \$US 53.17 per year, and in this case the lowest values for this variable and all scenarios was \$US 54.26 per year. It is important to note that the value reported by Ref. [15] corresponds to a "no tariffs" scenario, and our reported value −and developed scenario in this contribution− is for the case with "high tariffs". This means that values for inflation, WACC and electricity price are as important as tariff level since it is possible to produce similar results with different considered values for tariffs. That is, changes in specific uncertain parameters are able to produce comparable changes similar to those by implementing (or not) different tariff levels. Table 6 presents a full comparison of the worst and best values for decision variables in our work, to the solved case in Ref. [15].

An important observed aspect is that for some cases the minimum value for cumulative MSP and total local production is equal to zero, which indicates that the PV manufacturing design methodology allows for a supply of the PV demand without domestic production. Furthermore, in some scenarios, the import and export costs are equal to zero, which could mean that all PV demand (for the considered consumption regions) is met through the domestic PV manufacturing system. These solutions for specific scenarios (a solution for each scenario), however, might be a poor or infeasible solution for other scenarios, although they can still be used as comparison points for a global solution.

Fig. 6 shows the values for the cumulative probability and the composed objective function when the expected value for the composed function is maximized to find a solution where all decision variables are compensated, and a compromise is reached.

Each term in Equation (8) could be taken as the satisfaction value for decision variables, where a value of 1 means that variable has reached its target value while a value of 0 means that decision variable has reached its worst value. Therefore, if the compromise solution for each scenario is equal to 1, then all objectives are satisfied.

Fig. 6 shows the different values obtained for the compromise solution for all considered scenarios (see Equation (8)) when the expected value for the compromise solution (see Equation (9)) is maximized. Note that the manufacturing system topology is the same for every scenario, obtained from Equation (10) − (14). In this work we maximize the value for the expected compromise solution, subject to values of all scenarios for the uncertain parameters. Therefore, it is not possible to satisfy all decision variables simultaneously because the values for uncertain parameters are different while the topology is kept constant. If all decision variables were satisfied, then the value for the compromise solution would be equal to 1 (*i.e.*, no variable has to 'compromise' in reaching their objective and they all reach their optimum, hence the value of 1). For that topology −reached when the expected value is maximized−, the maximum value of the composed objective function is

Table 6
Worst and best case for decision variables for the manufacturing processing system. Reference case is reported by Ref. [15]].

Variable	Units	Worst case	Best case	Worst case reference	Best case reference	Solved case in reference
Global Minimum Sustainable Price	$US/W	9.02	0.74	17.58	0.71	0.71
Transportation Cost to Markets	Millions $US	411.57	54.26	410.30	53.17	258.61
Local Production	Millions MW	0	1.2422	331.77×10^{-6}	2.7267	0.09057
Exports Cost	Millions $US	3.8630×10^3	0	11,335	0	0
Imports Cost	Millions $US	6.7639×10^3	0	32,918	0	0
Local Transportation Cost	Millions $US	372.92	0	2498	0	6027

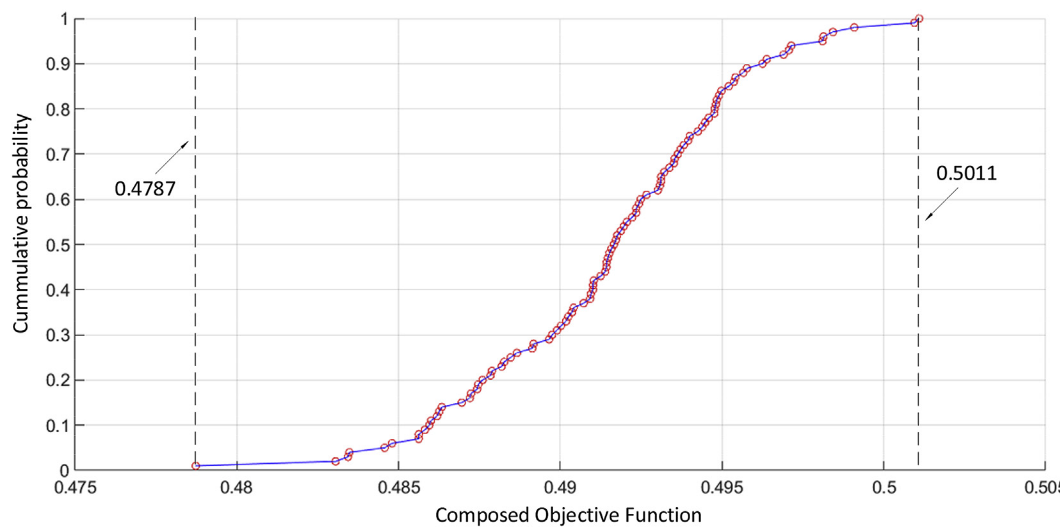

Fig. 6. Cumulative probability for PV manufacturing supply chain composed objective function for scenarios with uncertain parameters.

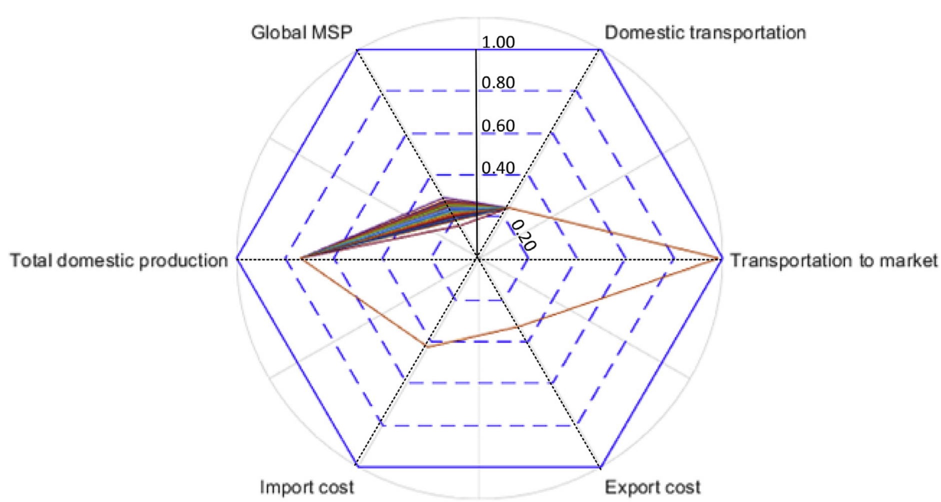

Fig. 7. Achieved satisfaction of decision variables based on solution for scenarios varying electricity price, inflation and WACC values.

0.5011 and the worst value for the composed objective function is 0.4787. This worst value is important because this value represents the worst case for the composed objective function when the expected value is maximized [21].

Furthermore, as mentioned, all points in Fig. 6 are subject to the same supply chain topology, the difference in composed function values is caused by the changes in uncertain parameters. The importance of comparing between best and worst cases is that decision makers could get the performance of a supply chain under a given range of values for uncertain parameters. Decision makers could then decide if they are able to support the worst case under given manufacturing system topology. Particularly, in this case, there is not a significant difference between best and worst cases since the ratio of the difference between best case ($OF_S^{composed} = 0.5011$) and the ideal case ($OF_S^{composed} = 1$), as well as the wort case ($OF_S^{composed} = 0.4787$) and the ideal case ($OF_S^{composed} = 1$) is equal to 0.9570 ((1–0.5011)/(1–0.4787)). Furthermore, Fig. 6 shows that under these values of uncertain parameters, the probability to obtain a high value for composed objective function increases almost constantly from a value of 0.485; in other words, there is a large probability of obtaining a composed objective higher than 0.485.

Fig. 7 illustrates the dissatisfaction value for each decision variable and scenario for uncertain parameters. The global MSP is seen to be directly affected by electricity price, inflation, and WACC values, as seen in Fig. 5 through standardized regression coefficient (SRC) method. This can be understood as the global MSP being the decision variable most sensitive to variations in values in each modeled scenario. Each line shown in Fig. 7 corresponds to one of the scenarios for these uncertain parameters (electricity price, inflation, and WACC), where each scenario corresponds to different values.

The transportation cost to market variable almost reaches its full objective value, while export and import costs attain values of around 40% of their objective values. In addition, domestic production achieves a high value and its satisfaction factor is almost 80% of its maximum possible value. This behavior indicates that the entire PV manufacturing system tries to meet optimum values of domestic production and transportation cost to markets in order to compensate dissatisfaction in other decision variables.

As previously mentioned in the mathematical formulation section, the PV manufacturing system should be the same for all considered scenarios since, under a realistic scenario, the supply chain topology cannot be modified nimbly once variations on electricity price, inflation or WACC; which is one of the main advantage of the mathematical model since it allows proposing a manufacturing system configuration independently of the value for uncertain parameters (configuration should be used for all values of uncertain parameters). In this regard, when the expected value of the composed objective function is maximized, the manufacturing system topology contains 7 Polysilicon producers, 16 Ingots producers, 17 wafer producers, 15 cells producers, and 2 PV modules producers. This number of PV supply chain nodes indicates that solution in PV manufacturing system tries to support different values for uncertain parameters and supply chain topology is diversified.

Fig. 8 shows the general distribution in Mexico for different selected PV supply chain nodes. The PV manufacturing nodes for ingot, wafer and cell production are distributed across the country, while nodes for PV modules production are fixed at two sites. Locations for PV modules producers could be associated to the distribution to external consumption regions because one of the sites is located in the northern region of country (border with USA), and another one is in the west coast of Mexico, corresponding to one of the most important sea ports and easiest access route to China.

Fig. 9 shows the states for PV manufacturing system nodes as well as the averaged (over 100 scenarios) distributed amount of goods targeted for domestic production. Also, Fig. 9 details the exported and imported amount of goods for the entire PV manufacturing supply chain.

We can observe in Fig. 9 that a domestic manufacturing system could satisfy all demand for considered consumption regions while exporting a significant portion of manufactured cells. Also, the PV manufacturing system utilizes a significant amount of polysilicon to increase domestic production of ingots, wafers and cells, increasing the benefits of economies of scale while reducing MSP.

To relate the resultant locations with uncertain parameters and compromise solution, it is essential to remember that compromise solution is a direct indicator of the satisfaction of proposed decision variables (global MSP, export cost, import cost, domestic production, domestic transportation cost and transportation cost to markets). Subsequently, we applied the SRC method for the uncertain parameters and the compromise solution. Fig. 10 presents the results for the square of the standardized coefficient (β^2), which is

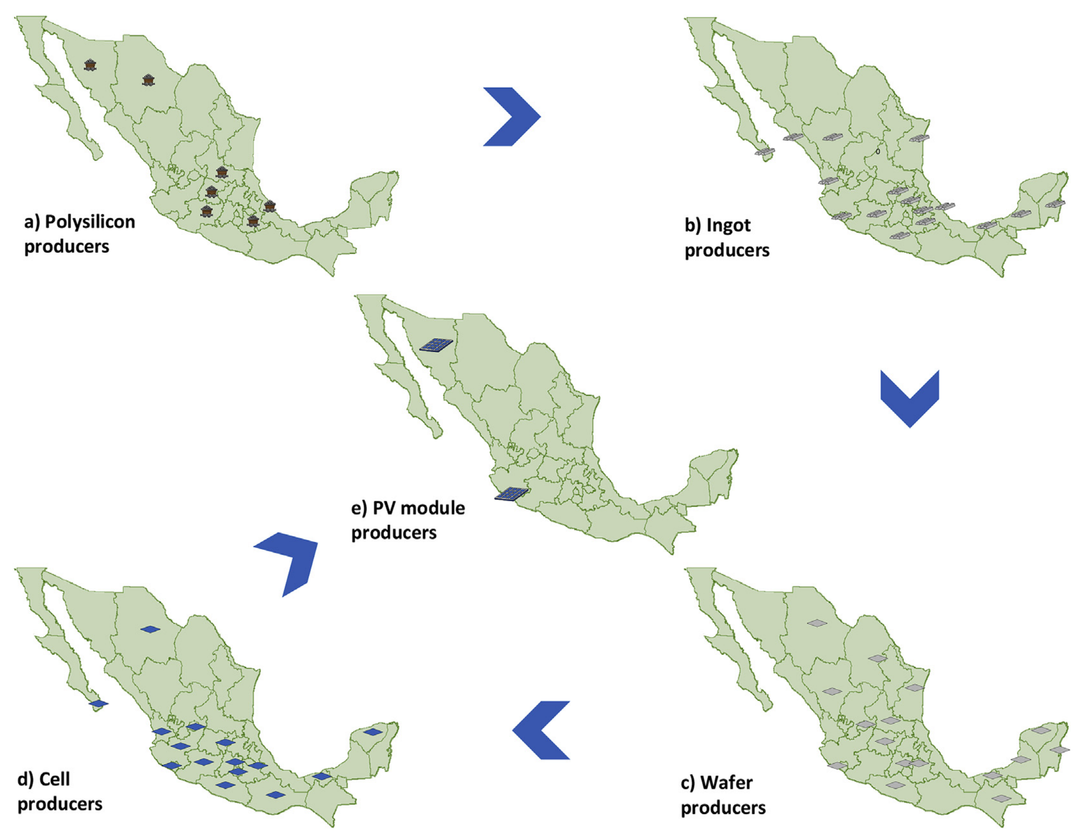

Fig. 8. General spatial distribution of PV manufacturing system nodes. a) polysilicon producers, b) ingot producers, c) wafer producers, d) cell producers and e) PV modules producers.

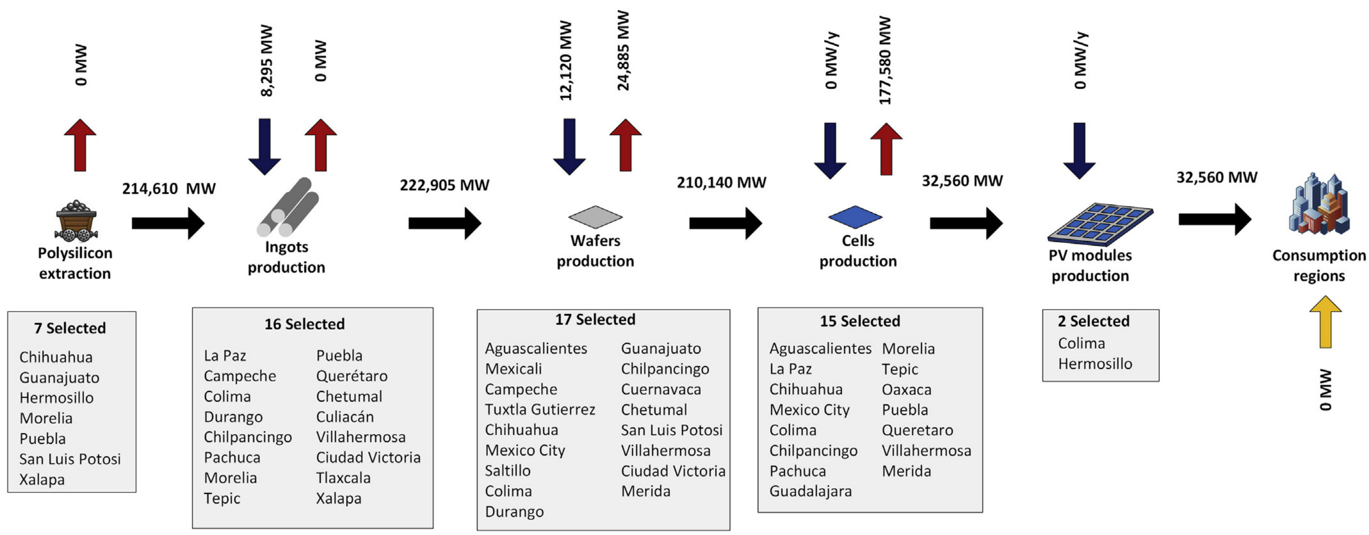

Fig. 9. General representation for PV manufacturing system for proposed approach.

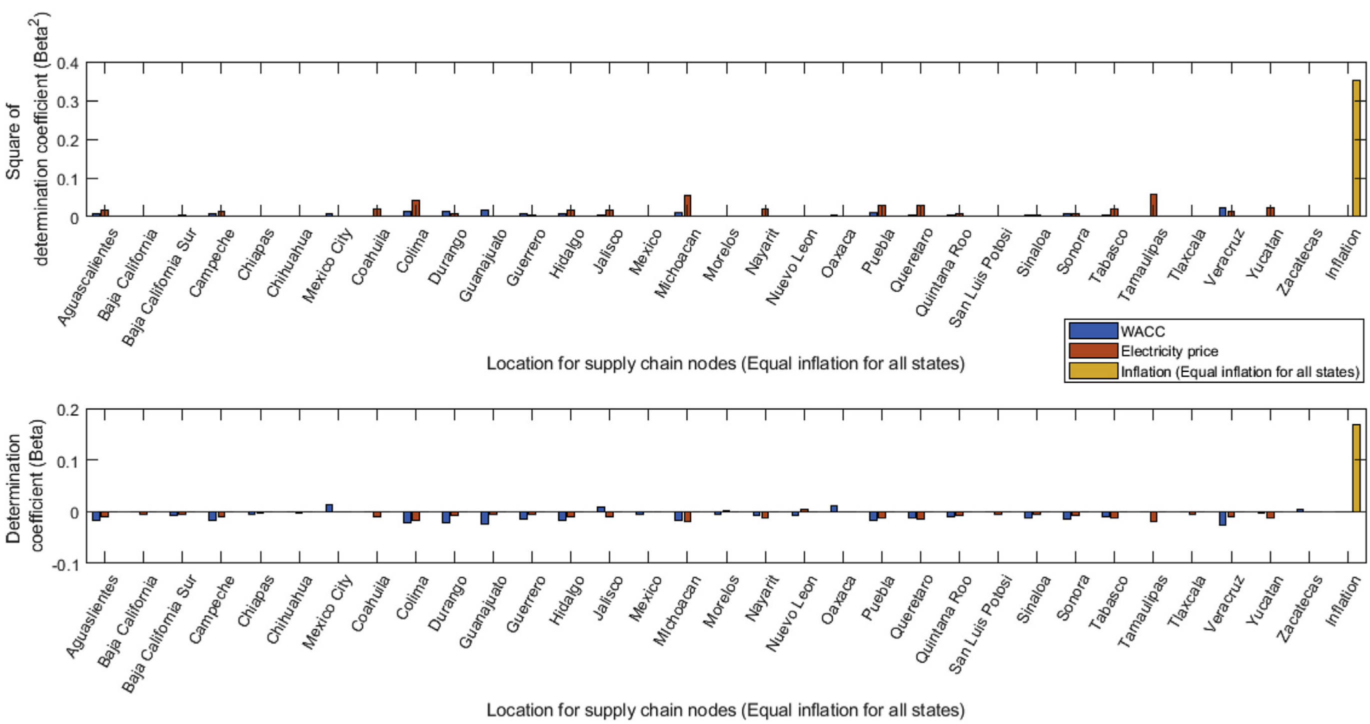

Fig. 10. Standardized Regression Coefficient (SRC) analysis for Compromise Solution regarding inflation, electricity price and WACC.

used to obtain the contribution to the compromise solution. Also, Fig. 10 shows the standardized coefficient (β) to indicate the direction of the contribution to the compromise solution each of uncertain parameters. The contribution is shown for each considered location.

WACC and electricity prices are set to be different on each location, representative of a typical behavior of an industry across different regions, but the inflation is set to be the same across the entire country. Therefore, each scenario considers a tuple of values for electricity price and WACC for each location. Fig. 10 shows the influence of these uncertain parameters over the compromise solution represented by the magnitude of the standardized regression coefficient and its square value.

We can see that inflation is the uncertain parameter with highest contribution to the satisfaction of decision variables (compromise solution), in fact, the square of standardized coefficient is around 0.35, while the contribution of other uncertain parameters is little higher than 0.05 in some cases. It is important to highlight that inflation did not contribute significant to the MSP function, but inflation is a parameter that affects all locations of supply chain nodes. For that reason, the contribution of this factor (inflation) is significantly higher than the others. In addition, we note that if WACC and electricity price increase, then the value of compromise solution decrease. Lastly, the correlation between uncertain parameters is significant because the determination coefficient is 0.9815 and these parameters have a direct relation due to a statistically significant *p*-value equal to 9.01×10^{-7}.

5.4. Computational resources and model's characteristics

The mathematical formulation was implemented in GAMS (General Algebraic Modeling System) software in a 16 GB RAM computer with a Processor i7 up to 3.20 GHz. The model in the first stage is a MINLP (Mixed Integer Non Linear Programming) problem, where upper and lower bounds are determined by 159,105 constraints, 109,189 continuous variables and 33,499 binary variables. CPU time consumed to solve each problem (maximization or minimization of decision variables presented in Eqs. (2)–(7)) varies from 2 to 24 h depending on each scenario. This drastic time difference might be caused by the dispersion of scenarios in full uncertain space, mainly because the supply chain configuration (final result of deterministic optimization problems) is strongly affected by the variation of the uncertain parameters (electricity price, WACC and inflation) which can be very complex in some scenarios and simple in others.

Furthermore, the mathematical formulation in which the expected value of the composed objective function (Eq. (8)) is maximized and subject to equal topology for all scenarios consists of 15,938,001 constraints, 10,919,138 continuous variables and 3,363,737 binary variables. As observed, the mathematical model size using all scenarios is drastically larger than mathematical model sizes for deterministic cases. Because of the mathematical formulation size, it is crucial to provide an initial start point to find a solution, which could be a disadvantage for the formulation. To address this matter, we used a starting point from previously obtained solutions since solutions for each scenario have been obtained in previous solution stages. The mathematical model was formulated as a MINLP problem and it was solved with DICOPT solver with MINOS and CPLEX as sub solvers. Because of the model size, some solver options were modified to improve the solver performance. Although finding a feasible solution under uncertainty consumes a considerable amount of CPU resources, the mathematical formulation under uncertainty provides a more robust PV manufacturing system topology.

6. Conclusions

In this contribution we presented a new scheme for PV manufacturing system planning considering diverse decision variables and uncertainty in significant parameters in the PV supply chain behavior, such as the inflation, electricity price, and WACC.

This work proposes a solution scheme considering several decision criteria, and where a composed objective function with different weights is implemented; although the weight for each variable is expected to change depending on the stakeholders' priorities, in this case, we have considered equal weights for all decision variables in order to reflect an equal and unbiased importance to of each of them.

Main findings of this paper concerning the consideration of uncertain input parameters such as electricity price, WACC and inflation is that this formulation allows one to propose a PV manufacturing system subject to several possible values for these uncertain parameters. Also, we observed that electricity price and WACC have a high contribution to MSP and even though inflation does not have a highly important contribution to the MSP value, the final compromised solution is strongly affected by inflation.

Our results indicate that if inflation increases, the satisfaction of decision variables increases too. It is worth pointing out that inflation is used in this model to compute the values for the Minimum Sustainable Price (MSP) in each processing stage. Therefore, if inflation varies, then MSP varies, too. Furthermore, it can be observed in Fig. 7 that the uncertain parameters (including inflation) mainly affect the MSP value. Concerning the model developed by Ref. [13]; which is used as basis for this work, we can state that if inflation increases, the MSP decreases, consistent with the results herein presented.

One of the most important applications of our proposed model is to develop market policies such as studying the impacts of tariffs or production levels for different products considering diverse economic parameters (inflation, electricity price and WACC). It also represents a tool to design targeted incentives, should a manufacturing base is to be stimulated. Moreover, this model can be useful to propose solutions about which parameters need to be modified if a determined behavior of the supply chain is desired. An updated version on the price components used in the techno-economic model would reflect current market prices in a significantly better way. The focus herein, however, has been the introduction of a stochastic framework to assess uncertainty in different input parameters.

The mathematical formulation was a MINLP where the nonlinearity is given by the economies of scale to define the MSP, which causes numeric difficulties for model solving. Additionally, the solution of the mathematical model was limited by the number of scenarios to consider under uncertainty.

Our presented approach was solved in two stages, where first one produce limits for used decision variables. Based on first stage results we can suggest that PV manufacturing systems are sensitive to the values of electricity price, WACC and inflations since the obtained values for decision variables in the optimal and feasible solutions are too different and, the CPU time changes drastically. The second solution stage has shown that at least a PV supply chain topology exists that is capable of supporting the variations between the considered uncertain parameters. The results presented illustrate the complex performance of PV supply chains when international and domestic factors are accounted, which highlight the importance of planning models —such as the presented in this work— to plan and adjust the PV supply chain configuration under different various plausible market conditions.

In comparing these results derived from a stochastic approach against deterministic formulations (presented by Ref. [15]) we can draw some important differences. The deterministic approach needs a lower amount of data collection than a stochastic formulation, but the data would need to have a better precision than data used in a stochastic approach because the formulation under uncertainty might consider a probable range for parameters instead of the exact data. In addition, the stochastic approach can provide a set of probable values for the objective function considered in a deterministic problem and elucidate more insights for decision makers and therefore render itself more useful for their use. Nevertheless, the stochastic solution could consume abundant computational (CPU) time to find infeasible (or bad) solutions, while a deterministic solution could be used as a starting point for the stochastic model.

Finally, a possible extension for this work could be to consider different tariff level and control strategies with different values for parameters over time in order to adjust the model to real and currently evolving cases in global policies.

Data availability

Datasets related to this article can be found at.

https://drive.google.com/open?id=1sSSQ-J8erR6KcJwbEPQYZiu6Y7qgb2TB.

hosted at José Ezequiel Santibañez-Aguilar, Sergio Castellanos, Antonio Flores-Tlacuahuac, Daniel M. Kammen, Tonio Buonassisi, Benjamin B. Shapiro, Douglas M. Powell, Used Data for Solar

Manufacturing. (2019).

Acknowledgments

The authors wish to thank the support from Mexican government agencies (ProMexico, SENER) with general data. Also, authors thank to Ian M. Peters for this point of view and suggestions provided during the developing of this paper. Castellanos, S. thanks support from Tecnologico de Monterrey through its BECI-ITESM fellowship. Santibañez-Aguilar, J.E., and Flores-Tlacuahuac, A. appreciate the financial support provided by the Mexican National Council for Science and Technology (CONACyT), Secretaría de Energía - CONACyT trough the Binational Energy Laboratory grant. Also, Santibañez-Aguilar, J.E., Flores-Tlacuahuac, A., and Castellanos, S. thank the Energy and Climatic Change Research Group at Tecnologico de Monterrey, Monterrey, Mexico.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2019.10.010.

We present the nomenclature used in the mathematical formulation. The nomenclature is divided in parameters, variables and binary variables.

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Nomenclature

Parameters

$d_{n4,n5}^{local}$: Distance between nodes n4 (domestic PV modules production nodes) and consumption regions n5
$d_{e4,n5}^{international}$: Distance between nodes e4 (global PV modules production nodes) and consumption regions n5
$d1_{n0,n1}^{Local}$: Distance between domestic nodes n0 and n1 (polysilicon extraction and ingots production nodes)
$d2_{n1,n2}^{Local}$: Distance between domestic nodes n1 and n2 (ingots and wafers production nodes)
$d3_{n2,n3}^{Local}$: Distance between domestic nodes n2 and n3 (wafers and cells production nodes)
$d4_{n3,n4}^{Local}$: Distance between domestic nodes n3 and n4 (cells and PV modules production nodes)
${}^{Lower}MSP^{global}$: Lower limit for global Minimum Sustainable Price
${}^{Upper}MSP^{global}$: Upper limit for global Minimum Sustainable Price
${}^{Lower}P^{Local}$: Lower limit for total domestic production
${}^{Upper}P^{Local}$: Upper limit for total domestic production
$TC_{n4,n5}^{local-markets}$: Unitary Transportation Cost between nodes n4 and n5
$TC_{e4,n5}^{international-markets}$: Unitary Transportation Cost between nodes e4 and n5
$TC_{n0,n1}^{Local-Si}$: Unitary Transportation Cost between nodes n0 and n1 for polysilicon
$TC_{n1,n2}^{Local-ingot}$: Unitary Transportation Cost between nodes n1 and n2 for ingots
$TC_{n2,n3}^{Local-wafer}$: Unitary Transportation Cost between nodes n2 and n3 for wafers
$TC_{n3,n4}^{Local-cells}$: Unitary Transportation Cost between nodes n3 and n4 for cells
${}^{Lower}TC^{Markets}$: Lower limit for total transportation cost to consumption regions
${}^{Upper}TC^{Markets}$: Upper limit for total transportation cost to consumption regions
${}^{Lower}TC^{Exports}$: Lower limit for exports cost
${}^{Upper}TC^{Exports}$: Upper limit for exports cost
${}^{Lower}TC^{Imports}$: Lower limit for imports cost
${}^{Upper}TC^{Imports}$: Upper limit for imports cost
${}^{Lower}TC^{Local}$: Lower limit for domestic transportation costs
${}^{Upper}TC^{Local}$: Upper limit for domestic transportation costs
ω_{MSP}: Weighting factor for Minimum Sustainable Price term in composed objective function
ω_{TCM}: Weighting factor for transportation to markets term in composed objective function
ω_{LP}: Weighting factor for domestic production term in composed objective function
ω_{TCE}: Weighting factor for exports cost term in composed objective function
ω_{TCI}: Weighting factor for imports cost term in composed objective function
ω_{LTC}: Weighting factor for local transportation costs term in composed objective function

Variables

$E[OF_s^{composed}]$: Expected value for composed objective function
$G_{j,t,s}^{inventory}$: Inventory level of any good in the production node j at the period of time t
$G_{i,j,t,s}^{intlet-local}$: Distributed good amount from previous production node i to production node j at the period of time t
$G_{ei,j,t,s}^{import-international}$: Imported good from previous international node ei to production node j at the period of time t
$G_{j,t,s}^{produced-local}$: Amount of produced good in the production node j at the period of time t
$G_{j,t,s}^{toprocessing-local}$: Amount of good to be sent to processing technologies in production node j at the period of time t
$G_{j,k,t,s}^{outlet-local}$: Distributed good amount from production node j to next production node k at the period of time t

$G_{j,ek,t,s}^{export-international}$: Exported good from production node j to next international production node ek at the period of time t
MSP_{s}^{global}: Global Minimum Sustainable Price
$MSP_{n0,s}^{Step0}$: Minimum Sustainable Price for polysilicon extraction node
$MSP_{n1,s}^{Step1}$: Minimum Sustainable Price for production node n1
$MSP_{n2,s}^{Step2}$: Minimum Sustainable Price for production node n2
$MSP_{n3,s}^{Step3}$: Minimum Sustainable Price for production node n3
$MSP_{n4,s}^{Step4}$: Minimum Sustainable Price for production node n4
$OF_{s}^{composed}$: Composed Objective Function
p_s: Occurrence probability per each scenario
P_{s}^{Local}: Total local production
$P_{s}^{Local-Si}$: Local production for polysilicon
$P_{s}^{Local-ingot}$: Local production for ingots
$P_{s}^{Local-wafer}$: Local production for wafers
$P_{s}^{Local-cells}$: Local production for cells
$P_{s}^{Local-PV}$: Local production for PV modules
$TC_{s}^{Markets}$: Transportation cost associated to consumption regions
$TC_{s}^{Exports}$: Overall Export cost
$TC_{n0,e1,s}^{Export-Si}$: Export cost for polysilicon from domestic node n0 to external production node e1
$TC_{n1,e2,s}^{Export-ingot}$: Export cost for ingots from domestic node n1 to external production node e2
$TC_{n2,e3,s}^{Export-wafer}$: Export cost for wafers from domestic node n2 to external production node e3
$TC_{n3,e4,s}^{Export-cells}$: Export cost for cells from domestic node n3 to external production node e4
$TC_{s}^{Imports}$: Overall import cost
$TC_{e0,n1,s}^{Imports-Si}$: Import cost for polysilicon from external node e0 to domestic production node n1
$TC_{e1,n2,s}^{Imports-ingot}$: Import cost for ingots from external node e1 to domestic production node n2
$TC_{e2,n3,s}^{Imports-wafer}$: Import cost for wafers from external node e2 to domestic production node n3
$TC_{e3,n4,s}^{Imports-cells}$: Import cost for cells from external node e3 to domestic production node n4
TC_{s}^{Local}: Domestic transportation cost
$TP_{n4,n5,s}^{local-PV}$: PV modules amount transported from domestic manufacturing system to consumption regions
$TP_{e4,n5,s}^{international-PV}$: PV modules amount transported from international manufacturing system to consumption regions
$TP_{n0,n1,s}^{Local-Si}$: Polysilicon amount transported from domestic production node n0 to domestic production node n1
$TP_{n1,n2,s}^{Local-ingot}$: Ingots amount transported from production node n1 to node n2
$TP_{n2,n3,s}^{Local-wafer}$: Wafers amount transported from production node n2 to node n3
$TP_{n3,n4,s}^{Local-cells}$: Cells amount transported from production node n3 to node n4

Binary variables

$y_{n0,s}^{Local-Si}$: Binary variable to define if production node n0 exists for scenario s
$y_{n1,s}^{Local-ingot}$: Binary variable to define if production node n1 exists for scenario s
$y_{n2,s}^{Local-wafer}$: Binary variable to define if production node n2 exists for scenario s
$y_{n3,s}^{Local-cells}$: Binary variable to define if production node n3 exists for scenario s
$y_{n4,s}^{Local-PV}$: Binary variable to define if production node n4 exists for scenario s
$y0_{n0}^{Local-Si}$: Binary variable to define that production node n0 exists for general PV manufacturing system topology
$y1_{n1}^{Local-ingot}$: Binary variable to define that production node n1 exists for general PV manufacturing system topology
$y2_{n2}^{Local-wafer}$: Binary variable to define that production node n2 exists for general PV manufacturing system topology
$y3_{n3}^{Local-cells}$: Binary variable to define that production node n3 exists for general PV manufacturing system topology
$y4_{n4}^{Local-PV}$: Binary variable to define that production node n4 exists for general PV manufacturing system topology