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Modelling supply risks in interdependent manufacturing systems: A case study

Omega, R.S.[a], Noel, V.M.[a], Masbad, J.G.[a], Ocampo, L.A.[b,*]

[a]Department of Industrial Engineering, University of San Carlos, Cebu City, Philippines
[b]Department of Mechanical and Manufacturing Engineering, University of San Carlos, Cebu City, Philippines

ABSTRACT

This paper proposes a supply-driven inoperability input-output model (SIIM) in analysing risks of manufacturing systems. The approach, derived from the Leontief's input-output model, was previously debated for its implausibility in analysing sectors in an economic system. This paper provides interesting insights in production risk analysis especially that the adoption of SIIM in micro-level systems particularly in manufacturing systems was not yet explored in the current literature. The resemblance of economic systems and manufacturing systems in terms of system components, input-output concept, and component-wise interdependencies makes the approach appealing and highly plausible. Thus, this work adopts SIIM in analysing the impact of supply perturbations in a manufacturing system brought about by natural and man-made disasters, economic shifts, and government policies. An actual case study was carried out in a manufacturing firm in the central Philippines and two scenarios were presented to illustrate the proposed approach. The proposed approach is highly significant for manufacturing and risk practitioners in formulating mitigation policies to achieve a resilient manufacturing system.

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**Corresponding author:*
laocampo@usc.edu.ph
(Ocampo, Lanndon A.)

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1. Introduction

Competition among manufacturing industries both at local and global contexts has been increasingly tighter today than in the previous decades. These industries have been implementing crucial strategic decisions in order to compete. Furthermore, to sustain competitiveness, managers must be critical in various manufacturing decision-making areas in the context of firms' benefits, opportunities, costs and risks. A significant input to any decision-making process in manufacturing systems is the analysis of risks brought about by disruptions of internal and external components where manufacturing firms are highly susceptible to. Organizations in general and manufacturing firms in particular must seek to understand the underlying effects of these disruptions; thus, making risk analysis and management an ongoing concern [1].

Various approaches on risk analysis of manufacturing at firm level have been proposed in domain literature but these methodologies are based on qualitative measures. The inoperability input-output model (IIM) developed by Santos and Haimes [2], an important extension of the award winning input-output model introduced by Wassily Leontief for risk analysis, assesses the inability of sectors to perform their intended functions known as 'inoperability' caused by external perturbations such as natural disasters, terrorism, epidemic diseases, among others [2]. On a macroeconomic scale, Santos and Haimes [2], Jiang and Haimes [3], Haimes et al. [4] and Santos [5] have successfully demonstrated the use of IIM for risk analysis of interdependent systems. The strength of IIM lies in its capability of handling the cascading effects of a final demand perturbation with interdependent system components, e.g. sectors in an economy. In contrast, the supply-driven IIM (SIIM) addresses the risks of possible changes in supply, also known as 'value-added perturbation'. Nevertheless, both demand-driven and supply-driven IIM analyses the impact of perturbations brought about by internal or external, natural or man-made processes [6]. While IIM was applied generally for risk analysis in economic systems, it may also work for other similar interdependent systems such as manufacturing systems as shown in current literature.

The main argument adopted in this work is that the assessment of potential losses of manufacturing systems brought about by external or internal disruptions can be addressed by performing risk analysis and assessment from a systems perspective. This approach is a significant input to organizational decision-making in general and in the evaluation of production processes in particular. At the manufacturing firm level particularly in production systems, demand-side perturbation is less plausible as individual processes rarely have final demand. Thus, supply-side perturbation is more relevant as sources of raw materials are highly susceptible to disruptions caused by external shocks, e.g. climate change impacts, man-made disasters. This study attempts to explore the application of supply-driven IIM in manufacturing systems as supported by the notion that supply-side perturbations are more relevant than demand-side perturbations. This promotes the application of SIIM in manufacturing risk analysis. While former approaches provide insights on this problem domain, they fail to provide a quantitative analytical framework which is highly significant in manufacturing decision-making. The motivation of adopting such methodology is in its strength to holistically evaluate the processes and examine risks from a systems perspective. A case study in a mosquito coil manufacturing system is reported in this work. The contribution of this study is in presenting a new methodological framework that holistically addresses risk analysis in manufacturing systems.

2. Literature review

2.1 Risk management in organizational decision making

Risk management is the identification, assessment, and prioritization of potential losses brought about by disruptions [1]. Allocating scarce resources in the most effective manner in order to reduce the impact of disruptions is now becoming a challenge for decision-makers [7]. Zobel [8] presented a model that highlights perceived trade-offs in defining disaster resilience of an infrastructure, organization, or any system which has been made possible through an adjusted resilience function and optimization model. Wang et al. [9] adopted graph theory approach in analysing vulnerability for interdependent infrastructure systems while fuzzy set theory has been used in assessing the impact of flooding [10,11]. On the other hand, IIM, an extension of Leontief's input-output model, has also been adopted as a tool to aid practitioners and researchers in risk analysis and assessment – an important component of risk management [7]. Nevertheless, risk analysis has always been an integral part of decision-making processes of any organization. In manufacturing firms, such disruptions caused by unavailable workers, machine downtime, shortage of raw materials, natural disasters, among others yield potential inoperability of a production process. Understanding risks and how to mitigate these impacts from a systems approach advances current knowledge on manufacturing resilience research.

2.2 Risk analysis with input-output model

The Leontief input-output model (IOM) describes the behaviour and relation of different economic sectors and the interdependencies among them. IOM identifies the key sector in relation to its dependence with the other sectors [12]. Typically, once an economic sector is prioritized, there comes a need to provide risk mitigation policies on the impact of undesirable events and production disruptions. The inherent structure of IOM which is to address interdependencies of systems in general makes it attractive in risk analysis. Prioritization of the key sector entails implementation of preventive measures, policies, and investments for development and improvement as well as reducing the impacts of risks [7].

In economic systems, an internal or external failure of one sector could make that sector unable to perform its intended functions. Furthermore, with the inherent interdependencies of economic sectors, the impact of this failure propagates to the entire system which may trigger system's dysfunction. Santos [5] coined the term "inoperability" for this phenomenon leading to a new perspective in systemic risk analysis. This leads to an emerging model developed by Santos and Haimes [2] and Jiang and Haimes [3] known as the inoperability input-output model (IIM) which is basically derived from the Leontief IOM. IIM is an extension of the widely-accepted input-output model which focuses on assessing the possible impacts of a sector disruption in an economic system.

2.3 Demand-driven inoperability input-output model

In 2004, Haimes and Jiang [3] founded an extension of IOM which is the IIM – a simple tool used to quantify the possible losses and impacts of man-made or natural disasters to a disrupted sector and to the entire system as well. The works on IIM generally focus on the demand-side inoperability which is expressed as the percentage of economic loss due to a change in final demand. This definition was established by Santos and Haimes [2]. The plausibility of the IIM has has gained interests among domain scholars such that extensions have been developed capable of analysing the effects of certain disruptions [13]. Several extensions have been reported in analysing the cascading effects of disruptions which may eventually help decision-makers in developing and implementing risk mitigation policies.

IIM focuses on the demand-side perturbation caused by external factors such as man-made disasters and natural calamities on economic systems. Using the widely used notations of the IIM, it can be constructed as

$$q = A^*q + c^* \tag{1}$$

where c^* is demand-side perturbation vector, A^* is the interdependency matrix, and q is the inoperability vector.

The demand-side perturbation vector represents the degree of change in demand due to a disruption. This can be calculated as 'as-planned' final demand $\hat{c}_i$ minus actual final demand $\tilde{c}_i$ of the same sector, divided by the 'as-planned' its production level $\hat{x}_i$ which can be written as

$$c^* = [diag\ (\hat{x})]^{-1} [\hat{c} - \tilde{c}] \tag{2}$$

The demand-side interdependency matrix, denoted by A^*, is associated with the Leontief technological matrix A and the 'as-planned' production vector $\hat{x}$. This can be obtained using

$$A^* = [diag(\hat{x})]^{-1}[A][diag(\hat{x})\ ] \tag{3}$$

The demand-side inoperability vector q can be expressed as the percentage economic loss of a sector due to a reduced final demand. The economic loss can be described as the difference between the 'as-planned' production $\hat{x}$ and the reduced level of production $\tilde{x}$. By normalizing economic loss in terms of the 'as-planned' production $\hat{x}$, q can be expressed as follows

$$q = [diag(\hat{x})]^{-1}[\hat{x} - \tilde{x}\ ] \tag{4}$$

With the general formulation of the IIM which is expressed in a matrix notation as $q = A^*q + c^*$ the inoperability can then be assessed and analysed.

IIM describes the cascading effects of a perturbation of interconnected sectors using quantitative values. Tan et al. [1] suggested that organizations must seek to understand such disruptions and be able to quantify their impact on the focal sector and to the entire system as well in order to formulate effective mitigation activities. IIM is able to assess the inoperabilities of interdependent sectors caused by disasters, terrorism, among others [2].

IIM has been widely used in different applications such as in evaluating the effect of terrorism attack [2], loss of natural resource inputs due to climate change [14], fuel issues [15], etc. Along with emerging applications of IIM, several hybrid approaches have been developed in current literature with IIM as its core. These include the application of IIM in economic sectors [16], application of IIM focusing on specific areas in a sector [17], developing different methodologies on measuring the maximum level of perturbation the sector or the system can tolerate [18], applications that highlight the analysis of impact propagation to the upstream and downstream sectors [19], using a different approach in translating qualitative information into quantitative data [20], risk-based applications of IIM and the development of other models to assess inoperability [7] as well as analysing the dynamic elements of the matrices used in IIM [21]. See Table 1 for a summary of the applications of IIM. Note that the list is not intended to be comprehensive.

Table 1 Applications of Inoperability Input-output Model (IIM)

Classification of application	References	Descriptions
Application of IIM in different areas of the economy	[16]	Used a multi-regional IIIM in transportation network
	[13]	Applied IIM to evaluate the impact of inoperability of international trade (IT-IIM)
Application of IIM in specific area in a sector	[17]	Focused on the role of inventory with respect to resilience and inoperability
	[22]	Used IIM to quantify the effect in supply chain network disruption
	[23]	Measured the efficacy of inventory due to perturbation
Used a different method to know the maximum level of initial perturbation the sector or system can withstand	[24]	Developed a risk index which is obtained in order to support the IIM in creating an action plan of a system
	[18]	Created a shock absorption index which measures the maximum level of initial perturbation the system is capable of absorbing so that the entire system will not be fully inoperable
	[25]	Developed functional dependency net analysis (FDNA) which determines the level of inoperability tolerable by the sector
	[26]	Sensitivity analysis through sensitivity index which can be carried out by computing fields of influence
Used another approach of IIM that further stipulate the interdependencies of sectors	[27]	Agent-based approach also is used to break down sectors into subsectors to further assess the inoperability of these interrelated sectors and the system as a whole
	[28]	Decomposition of preparedness problems done in order to calculate the trade-off between preparedness cost and resilience among regions
Focused on propagation analysis to the upstream and downstream sectors	[1]	Propagation analysis is used to know the impact of a certain perturbation to the downstream and upstream sectors
	[19]	Focused on the propagation of critical infrastructure interdependency
Translated qualitative information into quantitative data	[29]	Developed stockholder's influence expressed in terms of loss of a stakeholder functionality in a scenario
	[20]	Used fuzzy numbers that deals with imprecise values
Risk management application of IIM	[7]	Applied IIM and provided risk management measures to potential disruption
	[3]	Risk-based framework of IIM to have for a more effective risk management
Development a dynamic technical coefficient	[21]	Focuses on the temporary or permanent values of the technical coefficient
Dynamic inoperability input-output model	[30]	Focuses on the inoperability of sectors with respect to time

The application of IIM in assessing the impact of disruptions in economic sectors provides guidance to decision-makers and policy-makers in implementing policies, preventive measures, and other investments to reduce the impacts of risks. However, the framework of IIM is not only limited to macro-economic analysis. Being a systems approach, it is also applicable to other areas that can be represented as systems, e.g. in production systems with processes as subsystems. Production processes are the series of steps required in transforming raw materials into finished goods which can be analogously treated as sectors of an economic system. These processes generate outputs that become inputs to other processes in converting work-in-process inventories into finished goods. Consequently, production processes establish interconnections with other processes making the entire system an interdependent one. The strength of IIM lies in its capability in handling the cascading effects of a final demand perturbation to interdependent system components, e.g. sectors. In contrast, the supply-driven IIM (SIIM), which is an analogous methodology of IIM, investigates the risks of possible changes in supply or the so-called 'value-added perturbations'.

2.4 Supply-driven inoperability input-output model

The supply-driven static IIM (SIIM) was derived by Leung et al. [6]. SIIM is capable of quantifying the loss brought about by a value-added disruption or a supply perturbation of a certain component in a system and its effect to the other components. However, the implausibility of SIIM has become an emerging issue in current literature. However, in this study, its relevance in evaluating manufacturing process systems is presented. The SIIM is represented as

$$p = (I - A_s^*)^{-1} z^* \tag{5}$$

where p is the vector of the cost change in output due to value-added perturbation, A_s^* is the supply-based interdependency matrix, and z^* is the initial value-added or supply perturbation vector. Suppose that $(I - A_s^*)^{-1} = \left(b_{ij}\right)_{n\times n}$, and

$$z^* = diag(\hat{x})^{-1}(\tilde{z} - \hat{z}) \tag{6}$$

$$p = diag(\hat{x})^{-1}(\tilde{x} - \hat{x}) \tag{7}$$

$$A_s^* = diag(\hat{x})^{-1} A_s \, diag(\hat{x}) \tag{8}$$

The vector $\hat{z}$ is the value of nominal value-added and $\tilde{z}$ is the value of degraded value-added after perturbation. The computations necessary in carrying out the SIIM are analogous to those of the IIM.

SIIM has been adopted for uncertainty and sensitivity analysis of interdependent infrastructure sectors [31]. While IIM works for risk analysis in economic systems, it also works for other similar interdependent systems such as manufacturing systems. The relevance of SIIM is on analysing the interdependent components in a system, e.g. processes in a manufacturing system, where supply is more considered relevant than demand. SIIM is more suitable in analysing the risks in a manufacturing system because of the presence of value-added inputs such as the raw materials, labour, and machineries that are highly susceptible to disruptions. Consequently, SIIM is likewise more relevant than the IIM as supply disruptions are more prevalent in the context of manufacturing due to the limited final demand requirements of each individual processes. For instance, most manufacturing systems have final demand in their end-of-line processes rather than on individual processes. Thus, a final demand perturbation is considered trivial in this context. With this, value-added input disruptions characterize most manufacturing systems which are caused by man-made or natural disasters forcing input prices to rise.

3. Case study

3.1 Background of the Case Firm

Firm X is a mosquito coil manufacturing firm situated in central Philippines. It is one of the most competitive firm in its industry and has been a distributor for more than five decades. These mosquito coils vary in sizes, scents and effectiveness. Although these coils vary greatly in terms of composition and characteristics, their processes do not differ significantly. There are ten processes that these products generally undergo: vertical mixing, weighing, blending, kneading, stamping, air drying, tunnel drying, coil harvesting, spraying, and packing. Two scenarios are presented in this study to illustrate the application of IIM in the context of manufacturing systems and to quantify the impact of supply disruption of a process to the entire system. See Appendix A for the flow of processes of Firm X.

3.2 First scenario: *Coffee skin shortage due to tropical typhoons*

Coffee is known to be a natural insect repellent which makes coffee skin an essential material for the production of mosquito coils. The Philippines is one of the few countries that are capable of cultivating and growing four varieties of commercially-viable coffee namely Arabica, Liberia (Barako), Excelsa and Robusta. The agriculture and cultivation of crops in various types including coffee beans have been at risk over the last decade due to the fact that the Philippines has been struck by numerous disasters. Not only are the local farmers affected with this current issue, but also to the industries that need coffee products in its production [32]. In recent news, at least 116 hectares of coffee beans in 10 towns in Antique, located also in central Philippines were destroyed by Typhoon Haiyan, with local name Yolanda [33].

SIIM is used to analyse the effect of this disruption to the manufacturing system of Firm X which primarily acquires coffee skin from different parts of the country for its production. Given the possibility of a typhoon to strike the source of coffee beans, SIIM is used to quantify the loss in terms of cost-price change due to this possible value-added or supply disruption. A supposed 20 % price increase of coffee skin due to scarcity of supply which directly perturbs the blending process. Applying SIIM in the scenario makes it possible to see the effects of this perturbation to each of the individual production processes.

Having a 20 % value-added perturbation in blending process, caused by coffee skin shortage, results to relative cost-price changes to the other processes with final perturbation values shown in Table 2. The initial perturbation vector $z^*$is obtained by placing 0.20 in the blending process where the system is initially perturbed and 0 values for the rest of the entries which means that there are no initial perturbation in these respective processes. Final perturbation vector p was obtained using Eq. 5. The blending process obtained the largest p value because its value-added is directly and initially perturbed. Due to the initial perturbation in the blending process, the other processes in the system are also affected which can be observed by their final perturbation due to the indirect and direct interrelationships that they have with the blending process. Except for the vertical mixing process because it is a preceding process of the perturbed blending process. It has a zero value thus, a value-added change in the blending process does not result to a cost-price change in the inputs of vertical mixing. Since vertical mixing is the first process in the system, it does not require inputs from other processes, e.g. blending process. It can be also realized that the processes with direct relationship with the initially perturbed blending process have larger p values compared to the other processes.

Table 2 Value-added perturbation caused by coffee skin shortage

Processes	z^* (initial perturbation)	p (final perturbation)
Vertical Mixing	0	0.0000
Weighing	0	0.1981
Blending	0.2	0.3769
Kneading	0	0.1182
Stamping	0	0.0841
Air Drying	0	0.0828
Tunnel Drying	0	0.0251
Coil Harvesting	0	0.0247
Spraying	0	0.0232
Packing	0	0.0218

3.3 Second scenario: *Coal price increase due to mine collapse*

Mosquito coils need to be hard to serve its purpose well and be an effective repellent. Thus, the drying process play a crucial role in manufacturing these products. These coils go through the tunnel drying process with the use of a steam boiler which primarily consumes up to 3,240 kg of coal for every 912 pairs of coil. With the daily demand of coils, coal is considered one of the high-volume raw materials used in production.

Coals are obtained through mining. Mining however, is considered one of the most dangerous industrial activities globally as several disasters have occurred in mining industries which are very unpredictable in nature. At an open-pit mine of the largest coal producer in the Philippines, the western wall of the mine collapsed due to heavy rains and 13 miners were buried under the soil. This occurrence led to a four-month suspension of work in the firm as mandated by the Department of Energy of the Republic of the Philippines. Almost 94 % of the country's coal requirements is supplied by the firm and the suspension of the mining operation is believed to have a large impact on the market [34]. This resulted to a disrupted supply of coal to manufacturing firms in their operations which eventually increased the price of coal.

With the risk of recurrence, the scenario aims to look into the effect of the coal price increase to the mosquito coil firm's processes. A value-added perturbation of 36 % in the tunnel drying process is assumed which is caused by the increase in price of coal due to mining operation suspension. Results are shown in Table 3. It can be seen in Table 3 that the tunnel drying has the same percentage of perturbation in the initial and final perturbation, unlike the previous scenario, mainly because of the interrelationships it has with the other processes.

As seen in Appendix A the process flow of Firm X is generally straightforward thus the affected processes are those succeeding the perturbed process. These affected processes namely coil harvesting, spraying, and packing is not capable of contributing a perturbation to the tunnel drying process as this process does not require inputs from these processes. Hence, it is not dependent on these processes. Coil harvesting has a final perturbation value more or less similar with tunnel drying mainly because it directly receives the outputs of the tunnel drying process. Mindful of the concept of linear process flow or straightforward interrelationship of processes, processes preceding tunnel drying have no cost-price change values p since these processes (vertical mixing down to air drying) do not receive inputs from tunnel drying.

Table 3 Value-added perturbation caused coal price increase

Processes	z^* (initial perturbation)	p (final perturbation)
Vertical mixing	0	0.0000
Weighing	0	0.0000
Blending	0	0.0000
Kneading	0	0.0000
Stamping	0	0.0000
Air drying	0	0.0000
Tunnel drying	0.36	0.3600
Coil harvesting	0	0.3545
Spraying	0	0.3333
Packing	0	0.3128

3.4 Discussion

In SIIM, two different scenarios of value-added perturbations were presented in the case study. For Firm X, scenario 1 shows coffee skin shortage brought about by tropical typhoons while scenario 2 illustrates coal price increase due to a disaster in mining operations. Results of the scenarios have quantified the final perturbation or cost-price changes of the value of outputs of the individual processes. It can be observed that Firm X has several processes with zero final perturbation values due its straightforward flow of processes. The final perturbation value of a particular process other than the perturbed process depends on its relationship and dependence with the initially perturbed process and the other processes. If that particular process precedes the perturbed process with no feedback loop, the impact of the initial perturbation is zero; that is p is zero, since it does not receive inputs from the perturbed process. In contrary, succeeding processes of the perturbed process are affected and the impact decreases as the distance, in terms of sequence, of a process with the perturbed one increases.

In this case study, SIIM has been successfully implemented in analysing and quantifying the impact of supply or value-added perturbations to the directly affected process and its cascading effects on the other processes due to the interdependencies among processes. In this study, two scenarios are presented to further explore the applicability of SIIM in micro-level application, i.e. in manufacturing firms. For both scenarios, it has been shown that when a certain process is disrupted through a supply or value-added perturbation, it will inflict cascading effects to processes it has interrelationships with. The perturbation directly affects other processes the perturbed process has strong relationships with i.e. the proceeding process which needs the perturbed process' outputs and in contrary, yield small effects to processes that are weakly interrelated with the perturbed one. Therefore, the changes in the value of required output as manifested by the p values, which show the cascading effects of the initial perturbation, depend on the process being perturbed and its interrelationships among other processes.

4. Conclusion and future work

The supply-driven inoperability input-output model adopted in this work addresses risk analysis in an interdependent system which is an inherent characteristic of most manufacturing systems. Contrary to current literature and practice where risks are assessed on individual component of the manufacturing system, the proposed approach identifies risks taken from the perspective of analysing the system as an integrated structure of components. SIIM quantifies the risks of cost-price increase of manufacturing process outputs brought about by the increase in prices of process value-added inputs which may be caused by natural or man-made disasters. It simultaneously considers production processes as a system rather than isolating each process for analysis. From the study reported in this work, it can be inferred that SIIM effectively quantifies the actual impact on each process after a value-added perturbation has occurred. Results of this risk assessment process help manufacturing managers and practitioners in establishing policies and infrastructures that would eventually minimize the systemic risks. SIIM aids the firm's management and other manufacturing practitioners in risk analysis and in decision-making collectively. No approach in manufacturing systems research has been reported that has the capability SIIM framework has to offer and this is considered as the main contribution of this work in the literature of risk analysis and manufacturing research. The proposed methodology is considered to be most suitable for manufacturing firms rather than the demand-driven approach mainly because each process in a manufacturing system generally does not have any final exogenous demand unlike economic sectors where final demand of each sector is naturally present.

A number of future works can be implemented with the proposed framework. First, the impreciseness of the data used in the input-output tables is crucial in enhancing the quality of the results. To address this, fuzzy set theory may be applied where data values become fuzzy numbers with membership functions. Future work can be done on this area and then compare the results with the results reported in this study in order to assess the robustness of the proposed approach. Secondly, SIIM framework can be extended to a dynamic SIIM in order to assess the behaviour of process perturbations with time. The dynamic SIIM may have the capability in determining the time when the manufacturing system achieves a status quo after the occurrence of a disruption. Third, the proposed approach can be applied in understanding supply-side risks of a supply chain brought about by supply-demand uncertainty [35]. When supply chain risks are assessed, the proposed method may be able to quantify the risks associated with the individual members of the supply chain. An interesting future work might be the integration of the proposed approach with the current directions of a sustainable supply chain [36]. The assessment may be incorporated with supply chain analysis frameworks that address the trade-off of maximising customer service level and minimising work-in-process inventory as proposed, for instance, by Smew et al. [37]. Finally, the emerging concerns on cyber-risks generated from hackers, employees, competitors and malicious software [38] can be also addressed using the proposed approach.

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References

[1] Tan, C.S., Tan, P.S., Lee, S.S.G., Pham, M.T. (2013). An inoperability input-output model (IIM) for disruption propagation analysis, *Proceedings of the 2013 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 186-190, doi: 10.1109/IEEM.2013.6962400.

[2] Santos, J.R., Haimes, Y.Y. (2004). Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures, *Risk Analysis*, Vol. 24, No. 6, 1437-1451, doi: 10.1111/j.0272-4332.2004.00540.x.

[3] Jiang P., Haimes, Y.Y. (2004). Risk management for Leontief-based interdependent systems, *Risk Analysis*, Vol. 24, No. 5, 1215-1229, doi: 10.1111/j.0272-4332.2004.00520.x.

[4] Haimes, Y.Y., Horowitz, B.M., Lambert, J.H., Santos, J.R., Lian, C., Crowther, K.G. (2005). Inoperability input-output model for interdependent infrastructure sectors: Theory and methodology, *Journal of Infrastructure Systems*, Vol. 11, No. 2, 67-79, doi: 10.1061/(ASCE)1076-0342(2005)11:2(67).

[5] Santos, J.R. (2006). Inoperability input-output modeling of disruptions to interdependent economic systems, *Systems Engineering*, Vol. 9, No. 1, 20-34, doi: 10.1002/sys.20040.

[6] Leung, M., Haimes, Y.Y., Santos, J.R. (2007). Supply-and output-side extensions to the inoperability input-output model for interdependent infrastructures, *Journal of Infrastructure Systems*, Vol. 13, No. 4, 299-310, doi: 10.1061/(ASCE)1076-0342(2007)13:4(299).

[7] Anderson, C.W., Santos, J.R., Haimes, Y.Y. (2007). A risk-based input-output methodology for measuring the effects of the August 2003 Northeast blackout, *Economic Systems Research*, Vol. 19, No. 2, 183-204, doi: 10.1080/09535310701330233.

[8] Zobel, C.W. (2011). Representing perceived tradeoffs in defining disaster resilience, *Decision Support Systems*, Vol. 50, No. 2, 394-403, doi: 10.1016/j.dss.2010.10.001.

[9] Wang, S., Hong, L., Chen, X. (2012). Vulnerability analysis of interdependent infrastructure systems: A methodological framework, *Physica A: Statistical Mechanics and its Applications*, Vol. 391, No. 11, 3323-3335, doi: 10.1016/j.physa.2011.12.043.

[10] Lei, T., Liangyu, W., Rijia, D., Lijia, L. (2011). Study on the dynamic input-output model with coal mine safety, *Procedia Engineering*, Vol. 26, 1997-2002, doi: 10.1016/j.proeng.2011.11.2396.

[11] Jiang, W., Deng, L., Chen, L., Wu, J., Li, J. (2009). Risk assessment and validation of flood disaster based on fuzzy mathematics, *Progress in Natural Science*, Vol. 19, No. 10, 1419-1425, doi: 10.1016/j.pnsc.2008.12.010.

[12] Miller, R.E., Blair, P.D. (2009). *Input-output analysis: Foundations and extensions*, (2nd edition), Cambridge University Press, New York, USA, doi: 10.1017/CBO9780511626982.

[13] Jung, J., Santos, J.R., Haimes, Y.Y. (2009). International trade inoperability input-output model (IT-IIM): Theory and application, *Risk Analysis*, Vol. 29, No. 1, 137-154, doi: 10.1111/j.1539-6924.2008.01126.x.

[14] Tan, R.R., Aviso, K.B., Promentilla, M.A.B., Yu, K.D.S., Santos, J.R. (2015). Development of a fuzzy linear programming model for allocation of inoperability in economic sectors due to loss of natural resource inputs, *DLSU Business & Economics Review*, Vol. 24, No. 2, 1-12.

[15] Tan, R.R., Aviso, K.B., Promentilla, M.A.B., Yu, K.D.S., Santos, J.R. (2014). Fuzzy inoperability input-output analysis of mandatory biodiesel blending programs: The Philippine case, *Energy Procedia*, Vol. 61, 45-48, doi: 10.1016/j.egypro.2014.11.902.

[16] Pant, R., Barker, K., Grant, F.H., Landers, T.L. (2011). Interdependent impacts of inoperability at multi-modal transportation container terminals, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 47, No. 5, 722-737, doi: 10.1016/j.tre.2011.02.009.

[17] Resurreccion, J.Z., Santos, J.R. (2012). Stochastic modeling of manufacturing-based interdependent inventory for formulating sector prioritization strategies in reinforcing disaster preparedness, In: *Proceedings of the 2012 IEEE Systems and Information Design Symposium (SIEDS)*, 134-139, doi: 10.1109/SIEDS.2012.6215127.

[18] Tan, R.R., Aviso, K.B., Promentilla, M.A.B., Solis, F.D.B., Yu, K.D.S., Santos, J.R. (2015). A shock absorption index for inoperability input-output models, *Economic Systems Research*, Vol. 27, No. 1, 43-59, doi: 10.1080/0953 5314.2014.922462.

[19] Owusu, A., Mohamed, S., Anissimov, Y. (2010). Input-output impact risk propagation in critical infrastructure interdependency, In: *Proceedings of the 13th International Conference on Computing in Civil and Building Engineering*, Nottingham, UK.

[20] Setola, R., De Porcellinis, S., Sforna, M. (2009). Critical infrastructure dependency assessment using the input-output inoperability model, *International Journal of Critical Infrastructure Protection*, Vol. 2, No. 4, 170-178, doi: 10.1016/j.ijcip.2009.09.002.

[21] Percoco, M. (2006). A note on the inoperability input-output model, *Risk Analysis*, Vol. 26, No. 3, 589-594, doi: 10.1111/j.1539-6924.2006.00765.x.

[22] Wei, H., Dong, M., Sun, S. (2010). Inoperability input-output modeling (IIM) of disruptions to supply chain networks, *Systems Engineering*, Vol. 13, No. 4, 324-339, doi: 10.1002/sys.20153.

[23] Barker, K., Santos, J.R. (2010). Measuring the efficacy of inventory with a dynamic input-output model, *International Journal of Production Economics*, Vol. 126, No. 1, 130-143, doi: 10.1016/j.ijpe.2009.08.011.

[24] Benjamin, M.F.D., Tan, R.R., Razon, L.F. (2015). Probabilistic multi-disruption risk analysis in bioenergy parks via physical input-output modeling and analytic hierarchy process, *Sustainable Production and Consumption*, Vol. 1, 22-33, doi: 10.1016/j.spc.2015.05.001.

[25] Garvey, P.R., Pinto, C.A., Santos, J.R. (2014). Modelling and measuring the operability of interdependent systems and systems of systems: advances in methods and applications, *International Journal of System of Systems Engineering*, Vol. 5, No. 1, 1-24, doi: 10.1504/IJSSE.2014.060880.
[26] Percoco, M. (2011). On the local sensitivity analysis of the inoperability input-output model, *Risk Analysis*, Vol. 31, No. 7, 1038-1042, doi: 10.1111/j.1539-6924.2010.01574.x.
[27] Oliva, G., Panzieri, S., Setola, R. (2010). Agent-based input-output interdependency model, *International Journal of Critical Infrastructure Protection*, Vol. 3, No. 2, 76-82, doi: 10.1016/j.ijcip.2010.05.001.
[28] Crowther, K.G. (2008). Decentralized risk management for strategic preparedness of critical infrastructure through decomposition of the inoperability input-output model, *International Journal of Critical Infrastructure Protection*, Vol. 1, 53-67, doi: 10.1016/j.ijcip.2008.08.009.
[29] Hester, P.T., Adams, K.MacG. (2013). Determining stakeholder influence using input-output modeling, *Procedia Computer Science*, Vol. 20, 337-341, doi: 10.1016/j.procs.2013.09.282.
[30] Lian, C., Santos, J.R., Haimes, Y.Y. (2007). Extreme risk analysis of interdependent economic and infrastructure sectors, *Risk Analysis*, Vol. 27, No. 4, 1053-1064, doi: 10.1111/j.1539-6924.2007.00943.x.
[31] Xu, W., Wang, Z. (2015). The uncertainty and sensitivity analysis of the interdependent infrastructure sectors based on the supply-driven inoperability input-output model, *International Journal of Innovative Computing, Information and Control*, Vol. 11, No. 2, 615-625.
[32] Whiteman, H. (2014). Philippines gets more than its share of disasters, from *http://edition.cnn.com/2013/11/08/world/asia/philippines-typhoon-destruction/*, accessed January 4, 2016.
[33] Mondragon, A. (2013). Antique's agriculture still reeling from Yolanda, from *http://www.rappler.com/move-ph/46911-antique-agriculture-yolanda*, accessed January 6, 2016.
[34] Olchondra, R.T., Abadilla, D.D. (2015). 5 dead, 4 missing in coal mine collapse. Inquirer News, from *http://newsinfo.inquirer.net/705980/5-dead-4-missing-in-coal-mine-collapse*, accessed January 6, 2016.
[35] Li, M., Wu, G.-D., Lai, X.D. (2014). Capacity coordination mechanism for supply chain under supply-demand uncertainty, *International Journal of Simulation Modelling*, Vol. 13, No. 3, 364-376, doi: 10.2507/IJSIMM13(3)CO14.
[36] Seuring, S. (2013). A review of modeling approaches for sustainable supply chain management, *Decision Support Systems*, Vol. 54, No. 4, 1513-1520, doi: 10.1016/j.dss.2012.05.053.
[37] Smew, W., Young, P., Geraghty, J. (2013). Supply chain analysis using simulation, Gaussian process modelling and optimisation, *International Journal of Simulation Modelling*, Vol. 12, No. 3, 178-189, doi: 10.2507/IJSIMM12(3)4.239.
[38] Očevčić, H., Nenadić, K., Šolić, K. (2014). Decision support based on the risk assessment of information systems and Bayesian learning, *Tehnički vjesnik – Technical Gazette*, Vol. 21, No. 3, 539-544.

Appendix A

Process flow of Products of Firm X