Cyber-Physical Systems based smart manufacturing of disinfectants: A need, and solution driven by COVID-19 Pandemic

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Abstract. Cyber-physical systems and Industry-4.0 have made smart manufacturing possible. The multi-national companies were able to quickly adapt and cope with changing times, but the micro small-scale enterprises (m-SMEs) were at crossroads to adopt new technology due to extensive costs involved. This gap of no existing solutions for micro-SMEs is the result of literature survey for this work. Then the COVID-19 pandemic made it extremely difficult for micro-SMEs to survive. This paper implements a smart manufacturing solution for production facility at one such micro-SME. Pre-pandemic, their facility had enough production to satisfy the demand, but pandemic overwhelmed their production with rapid rise in demand. The main goal for this study is to make the micro-SME cope this unprecedented rise in demand. The production facility was upgraded, and smart features were incorporated based on cyber-physical production systems framework to predict demand and transform a manual manufacturing into smart manufacturing. With more than one product being produced, optimum production was achieved avoiding over/underproduction for different products given the limited storage capacity available with the micro-SMEs.

Keywords: Smart Manufacturing; Cyber-Physical Systems; Small scale enterprises; AI; COVID-19.

1. Introduction

Smart manufacturing has rapidly spread across the manufacturing industry in last one and a half decade. Smart manufacturing as defined by Lu et al [1] as a fully integrated and collaborative manufacturing system that responds in real time to meet the changing demands and conditions in the factory, supply network, and customer needs. Where on one hand the MNEs (Multinational Enterprises) can cope up with this disruptive industrial revolution, on the other hand there are many micro small-scale enterprises (m-SMEs) which have faced difficulties in keeping up with the pace the industrial revolution has gone ahead with. This has meant that either m-SMEs have already faced or will soon face problems when their competition who do opt for the rise in technology will start gaining advantage over them. Not only competition from similar scale enterprises, but the competition will also be fierce as the new industrial revolution enables large scale enterprises to capture small scale markets as well. The current literature archives have a plethora of work dedicated to smart manufacturing and related topics such as CPS and I4.0. Most of these works have focussed on detailing out roadmaps, maturity models, architectures and frameworks of smart manufacturing specifically addressing needs for MNEs only. The unprecedented COVID-19 situation brought about the need for this existing enterprise to adopt the smart manufacturing transformation, the pandemic made it difficult for the enterprise to continue the usual practice of their production and think out of the box to keep up to a whopping rise in demand of their product due to the pandemic. Smart manufacturing has gained a lot of importance all over the world and enormous amount of work is being done to bring this into reality. Latest advances, new and improved products, services, and software have all been made available at an early stage for adoption of I4.0 to all concerned. The new industrial revolution has led to possibilities of mass customization [2] and mass personalization [3]. Termed as I4.0, this revolution has many significant terms one of which is smart manufacturing [4, 5]. A survey conducted to find out the transition of mechatronic systems into CPS [6] listed out design, models, simulations for CPS. A cyber physical manufacturing cloud (CPMC) mainly focussing on visualization of the CPS [7] was presented as a monitoring system or testbed for CPS. A recent work on CPS based transformation of existing legacy machines is available in literature [8]. Malhotra et al [9] gave an architecture of CPS for smart manufacturing. The background check concludes that the literature has largely provided conceptual frameworks and models of smart manufacturing and CPS. Lack of CPS enabled smart manufacturing and its implementation is evident. A lack of existing research work for enabling SMEs (especially micro businesses) into smart manufacturing exists giving quest for this work and the novelty behind it. The paper is structured as follows: Section 1 is introduction and includes literature review, introducing the micro-SME and describing the current state-of-the-art. Section 2 describes the proposed solution, Section 3 provides the results with relevant discussions, Section 4 concludes the paper with acknowledgements in Section 5 followed by References.

1.1. The micro-SME

This work focuses on a micro-SME which produces disinfectants without any Industry 4.0 technologies and demand to supply balance had been manageable until the COVID-19 pandemic. The demand due to pandemic rose drastically and the production went always on a 100% capacity making it difficult to manage demand and supply balance for different products and multiple customers at the same time. The same is true for any facility which has one or more than one product and have multiple customers placing orders for one or many products in different quantities as per their needs. With unprecedented situation customer orders became more frequent and demand very high leading to delays.

1.2. State of the art

Figure 1 schematically shows the state in which production facility was operating before the pandemic. An operator is tasked to manually mix the ingredients in the final mixing tank which. Being an m-SME, a limited storage facility is available. Therefore, with this storage facility and the manual operation, the company usually fills all the storage tanks with one type of product leaving less room for flexibility if there is a demand for a different product type. Product type A and product type B are taken as examples to show flexibility issues with manual production setup.

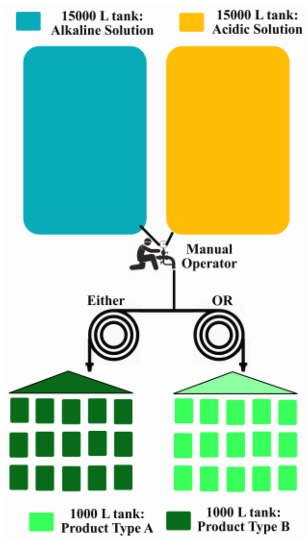

Fig. 1. Pre-COVID state of m-SME production facility.

The COVID-19 pandemic meant that current practices were all outdated and demand was so high that it became impossible for current production rate to meet the demand. However, if a facility was smart it had a better chance to cope up with this sudden rise in demand to at least bridge the gap between demand and supply in a smart manner. If the facility were not smart it would be completely in a disarray. Not to say the human decision makers are not smart enough to manage the production as much as they could but was it enough is the question. This led to current work focussing on providing a solution that will enable the company to better manage their production according to the specific demands of individual customers. A CPPS framework [10, 11] which can guide the industrial organisations to either newly create or upgrade existing manufacturing facilities into facilities compatible with Industry-4.0 has been referred in this work to transform the micro-SME facility into an automated one and then smart features were incorporated.

2. The proposed solution

For this work, the existing manual setup at the facility was revamped with industrial PLC based automated system that replaced the manual tasks to scale the production volume up and be compatible with smart features of a cyber-physical system (CPS) to enable smart manufacturing functionalities. Figure 2 shows a schematic representation of the revamped system displaying the automated system replacing manual operator.

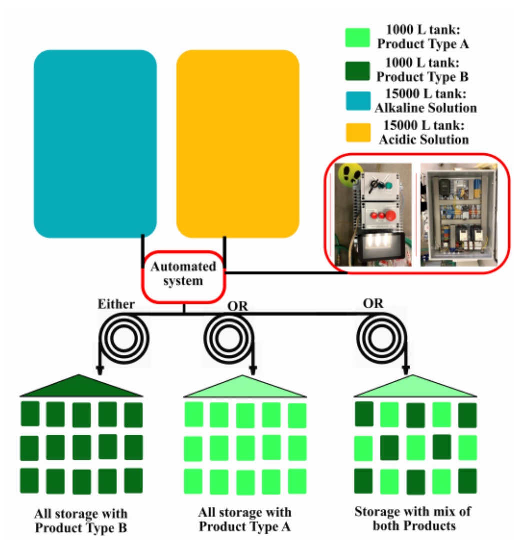

Fig. 2. Automated production system

The current work proposes a solution for smart manufacturing for m-SMEs and to make the solution generic and be applicable to various other m-SMEs some assumptions and pseudo scenarios have been made. In this work it is assumed that the company makes two products viz. Product-A (P_A) and Product-B (P_B). The demand for these products can come from various places such as hospitals, malls, public transport stations etc. For this work, only hospitals are assumed as customers as during the COVID-19 pandemic these were the ones hugely in demand and therefore four customers are assumed which are Hospital-1 (H_1), Hospital-2 (H_2), Hospital-3 (H_3), and Hospital-4 (H_4). The consumption at customer end is related to COVID-19 confirmed positive cases for hospital floors that relates to Product-A, and ambulance visits which relate to Product-B. If there were more positive cases during a day, then this meant that more movement of COVID-19 positive patients took place on floors and hence more cleaning was required and done. The COVID-19 data was publicly available on govt. website, we developed algorithms using Python scripts to access daily COVID-19 data and extracted the daily change in COVID-

19 positive patients and ambulance attendances in four customer areas mapping one each with H_1, H_2, H_3, and H_4. This enables us to define the product consumption and consequently the demand for the two products from each customer.

3. Results and Discussion

Figure 3a is a plot of daily COVID-19 cases across the four hospitals and Figure 3b is a plot of daily ambulance visits to attend COVID-19 calls. A schematic representation of how the pre-COVID production facility was working is provided in Figure 4.

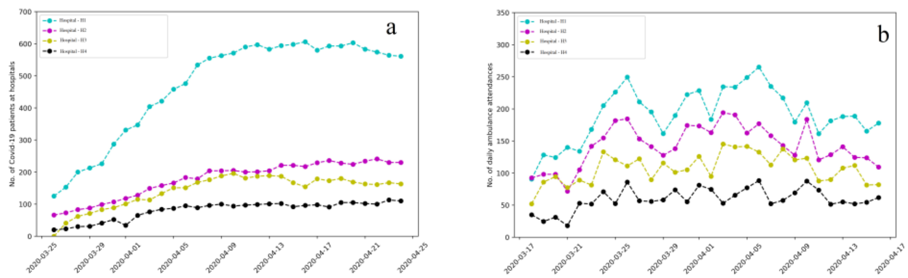

Fig. 3. The daily data across the four hospital regions (a) +ve cases, (b) Ambulance visits.

Figure 5 shows the same production facility operating amidst COVID19 pandemic and how the production stats were affected by the unprecedented situation. The production was same as in pre-COVID era, but the demand rose sharply due to rise in COVID cases (from Figure 3). This unprecedented demand was much more than the amount of each product being produced by the m-SME production facility and hence resulted in negative inventory as seen in Figure 5. With an automated system the capacity of producing the two products increased considerable and production stats with the automated system during COVID-19 was revamped, the same is shown in Figure 6 respectively.

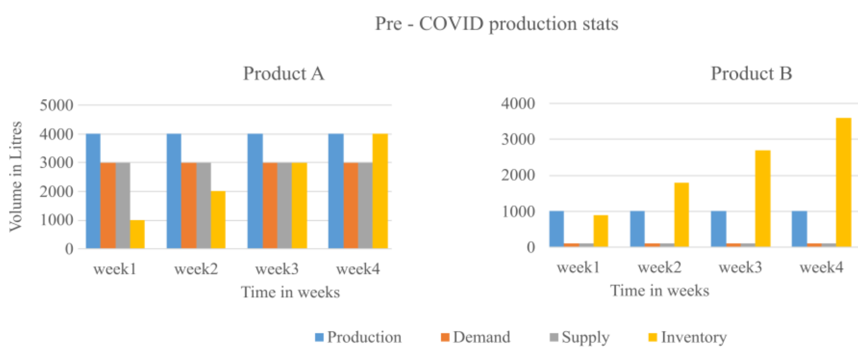

Fig. 4. Production stats for products A and B before COVID-19.

This mismatch between product A having a positive inventory (i.e., overproduction) and product B having negative inventory (i.e., under production) can be managed but with a manual think tank this is difficult to avoid. After developing the automated production system and understanding that there is a need for smart manufacturing solution to better predict demand, a production scheduling work was needed and has been developed. A linear regression model was employed to study the trends of COVID-19 cases and product consumption related to it. The model was then used to predict COVID-19 cases and thus product demand for coming week.

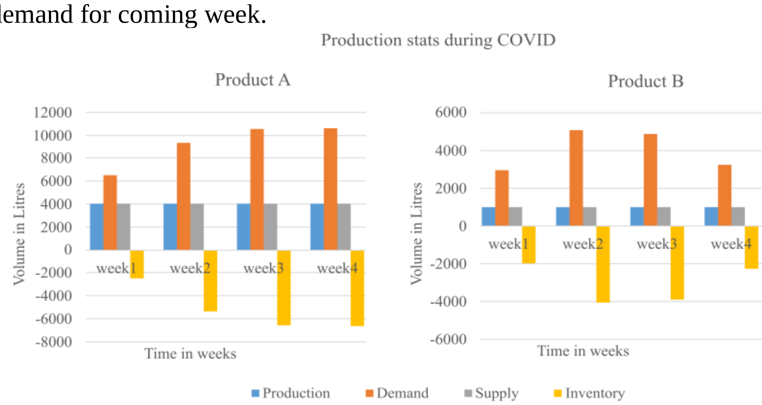

Fig. 5. Production stats for products A and B during COVID-19 with existing facility.

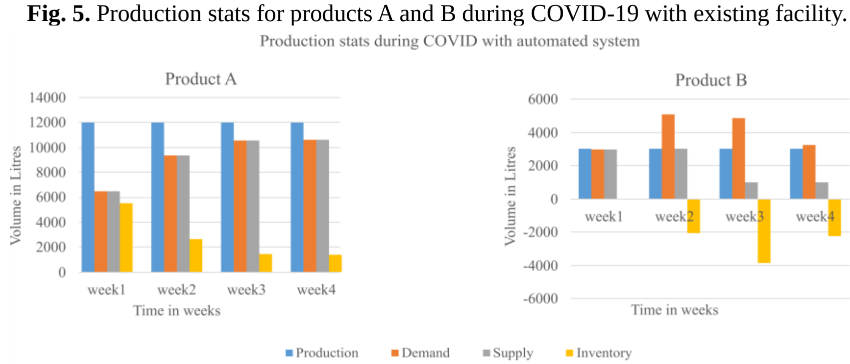

Fig. 6. Production stats for products A and B during COVID-19 with automated system.

Figures 7a and 7b shows the model fit on training data, predicted data and actual future data for COVID-19 cases and ambulance visits. Based on the model predicted, the predicted data slightly differs from actual future data in case of H1 but in case of the other three hospitals the predicted data and actual future data are quite similar. The misfit in case of H1 is due to this region being very big and various factors affecting the COVID cases in this area. Important thing to note is that with more training data in coming weeks even this error can be further reduced. Based on the predicted data, the production is also scheduled for these requirements. Trials were conducted for smart manufacturing production in a demo setup. The demo setup is a scaled down version of the main production facility and directly proportional to the volume scales of a full-scale production system. A small percentage of safety production is added to ensure production demand gap is as small as possible. Figure 8 is a graphical representation of production trial stats based on smart manufacturing predicted schedule on a day-to-day basis.

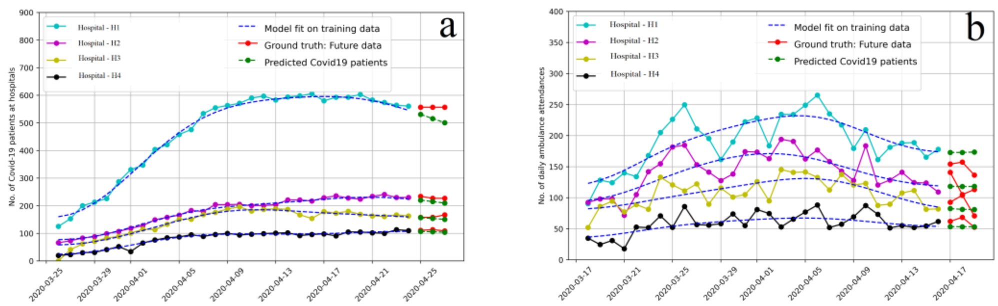

Fig. 7. Proposed model predictions for daily Covid-19 cases (a) product A, (b) product B for next 3 days across four hospital regions

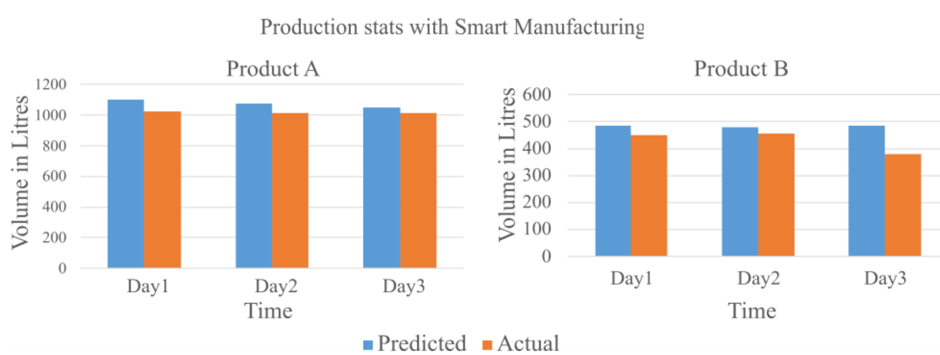

Fig. 8. Production stats based on scheduled smart manufacturing.

As seen on the figure the predicted volume of products A and B is well within the storage capacity available within the m-SME and the actual demand volume is just inside the predicted volume. The predicted volume is derived from the predicted COVID19 cases and ambulance visits and to overcome any prediction error the production includes 10% factor of safety to ensure there is no under production. Minor amount of both products overproduced are due to the factor of safety which is a negligible amount. The whole solution has addressed the gap in literature which had no smart manufacturing solution for the micro-SMEs.

4. Conclusion

The following points conclude the work:

- This work brings out a smart manufacturing solution for micro-SMEs which was not there in the archival literature.
- The theoretical contribution is simple techniques used to predict demand and schedule production at micro-SME facility to have optimum production.
- The work still has limitations such as it is applicable to limited customers and 2 products at a time only.
- A future scope of this work would be to better strengthen this solution for more customers and products included.

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