RandomForest Enabled Collaborative COVID-19 Product Manufacturing/Fabrications

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Abstract

Manufacturing COVID-19-related products such as face masks, shields, ventilators, shoe covers, gowns, and so forth, rapidly increased in recent months as the virus pandemic surges across the globe. Governments and Industrialists are keen to formulate quick decisions and are open to decentralize productions within a prescribed time limit using smart techniques. Recommendations on the volume of productions and the producer assignments are remaining a sole concern for policymakers or smart city authorities due to the unforeseen or unpredictable nature of the raging pandemic. This article introduces a RandomForest-assisted Collaborative COVID-19 Product Manufacturing (RFCCPM) framework. It collaboratively decides on producing COVID-19 preventive kits in a cost-efficient manner. The approach was experimented at the IoT cloud research laboratory; it achieved a manufacturing cost efficiency of 66 percent when Threshold Accepting (TA) algorithm was incorporated in the framework.

Keywords

COVID-19, RandomForest, Fabrication, Manufacturing, Smart Decisions

1. Introduction

One of the great health-related pandemic that has clouted all growth sectors, including manufacturing and the world finance sector, and has unsolved challenges is the lethality due to the COVID-19 public crisis. The virus has predominantly led nations to unwelcoming social distancing practices, ineffective communications, sweeping economies, discriminations in certain locations, distrustful relationships, and so forth, at large.

The Manufacturing/Fabrication sector has seen a disrupted shift in productions which remains as an unpredictable realization by manufacturers in order to revamp productions due to the ongoing lockdown and minimal employee situations in production units. High-quality machines have become non- operational for months since the eruption of the pandemic across the globe. Many manufacturing companies have almost closed their operations due to reduced workforce and erupting supply chain disruptions. Even the most urgent production of COVID-19-related preventive products such as masks, face shields, hood caps, shoe covers, and so forth, has witnessed a catastrophe which could adversely reiterate until innovative solutions are framed in the manufacturing/fabrication sectors. A single manufacturer of a region could not produce/supply all required COVID-19 products with utmost satisfaction in a short period in the midst of the exponential growth of COVID-19 cases.

The manufacturing sector, typically, attracts a major portion of revenue in various countries when compared to services or retail sectors. Accordingly, governments and manu-

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facturers are keen to provide solutions and upsurge productions at about 3 to 5 percentage in order to combat the anticipated economic consequences. However, the most crucial challenges faced by manufacturers, including COVID-19 product developers, during the COVID-19-crisis epoch are listed as follows:

- an abrupt stalemate in material movements, especially while transferring materials from international hubs or lockdown locations, due to disruption in the supply chains;
- a poor quality in COVID-19 solutions while adopting expeditious innovations with limited machinery or experiments in a short period from restricted lockdown locations;
- a differing working environment, especially the concept of "Work from Home" which urged a limited access to remote manufacturing sites; and so forth.

A growing volume of research and product development rapidly emerged globally to counterfeit the COVID-19 crisis and associated challenges apart from the core medical solutions. For instance, solutions relating to the digital working environment, adopting a long term planning for cash/resource utilization, delivery management, agile production of health-related products, and so forth, proliferated to improve the near future economic catastrophe.

Health departments and concerned officials of smart cities are eager to proactively develop COVID-19 preventive kits and protect the residents as healthcare resources, including hospitals and doctors, are scarcely available to nurse the exponentially growing patients. However, manufacturing the preventive kits has challenges – i.e., the following research questions need to be clarified / addressed for improving the voluminous productions: i) Which company needs to be permitted to develop COVID-19 products? and ii) How much quantity of COVID-19 products is required in a particular region considering the increase of the COVID-19 cases?

This article proposes a Random Forest (RF) algorithmic approach to predict the required number of productions of COVID-19 preventive kits based on i) the demand of a particular location, ii) COVID-19 quarantine cases, and iii) the budget availability of a region. It introduces a RandomForest-assisted Collaborative COVID-19 Product Manufacturing (RFCCPM) framework. The proposed RFCCPM approach includes a Threshold Acceptance (TA) scheduling algorithm in the framework to prepare a manufacturing schedule that considers the geo-distributed nature of collaborative manufacturing for quick voluminous productions. The RFCCPM framework has the capability to initiate production and promotes economy during COVID-19 or similar health-related crisis of the future. It maps production tasks to available or functional manufacturing hubs/units using a Threshold Accepting (TA) algorithm with the objective of improving the cost efficiency of manufacturing units. It can consider the lockdown situation of a region while producing products.

The proposed research was experimented at the IoT Cloud Research laboratory and observed the prediction accuracy of around 98.4 percent while predicting the COVID-19 quarantine cases of Kerala state using the RandomForest algorithm; and, the manufacturing cost efficiency of 66 percent while incorporating TA algorithm in the framework for preparing the manufacturing task schedule. In short, RFCCPM paves way for a cost- efficient production of products considering the availability of minimal employees during pandemic epochs such as COVID-19. The major contributions of the proposed work, as discussed in this paper, include the following:

- RFCCPM, an RF-assisted manufacturing framework, was developed for producing COVID-19 products, including preventive COVID-19 products such as face masks, face shields, hood caps, and so forth, understanding the increase / decrease of COVID-19 cases of a region;
- the application of RFCCPM was experimented considering fourteen MSMEs of the Kerala state of India; and,
- the Threshold Accepting (TA) algorithm of the framework was analyzed – i.e., the experiments revealed the cost- efficiency of 66 percent while producing COVID-19 preventive kits.

The rest of the paper is described as follows: i) Section 2 explores the state-of-the-art research in the application of RandomForest considering COVID-19 situations; ii) Section 3 discusses the inner details and functionalities of the deep-learning assisted collaborative manufacturing platform; Section 4 investigates into the theoretical aspects of improving the cost involved in the production of COVID-19 products while incorporating RFCCPM framework; Section 5 discloses the experimental results that were carried out at the "work at home" working environment by accessing the machines of the IoT cloud research lab; and, Section 6 consolidates the findings and insights of the proposed work along with a few future developments.

2. Related Work

Corona Virus 2019 (COVID-19) has marked its footprint in over 200 countries with severe acute respiratory syndrome which affected tens of millions of people. WHO has reported that 10021401 COVID-19 cases were reported across the globe with a total 499913 number of deaths as on 29 June 2020 [11].

Tens of thousands of innovations and mechanisms have been initiated in the recent past using AI [19], [32], [2], and the other innovative machine learning technologies. For instance, prediction models such as Deep Neural Networks have been applied to study the increase of COVID-19 patients and the curing status of different countries [8]. Authors of [16] have predicted the number of probable deaths that happen in the tenth day due to COVID-19.

A few researchers have applied prediction models to study the transmission pattern of the COVID-19 virus. For instance, authors of [20] have proposed a compartmental model to classify the transmission patterns of the virus; authors of [5] have applied long short term memory (LSTM) models to analyze the risk involved in the spread of the virus; similarly, authors of [3] applied LSTM models to differentiate corono-virus from the other respiratory diseases such as *pneumonia*. In [14], authors developed a mobile-enabled contact tracing mechanism to avoid COVID-19 contacts. Authors of [1] have proposed a method to improve the CNN training model as sufficient COVID-19 images were not available in the early period of the virus outbreak.

It is a known fact that the impact of COVID-19 highly affected the mobility of humans. The speed in spreading the virus and the severity of occurrence differed from region to region. This puzzles almost all solution architects [21]. The travel patterns changed as people were led to commotions [23]. In [29], authors studied the impact of lockdowns in three University campuses of their vicinity; the authors revealed the successive progress in the network traffic patterns due to the discharge of lockdown policies. In addition, approaches were devised to engage human resources efficiently using online systems, preferably by social media [24] considering the lockdown and other idleness factors of cities. Notably, authors of [4] devised a value chain considering the lockdown locations.

Many researchers and practitioners agree that online tools, including collaborative tools, would become a mandatory point of sale for overriding the emerging lockdown situations in cities [31]. Authors of [7] expressed the importance of a telemedicine approach in order to protect the medical practitioners and non-COVID-19 patients while pursuing consultations. A few researchers adopted measures to counteract the security challenges of online platforms such as Facebook, Twitter, Whatsapp, Zoom, Chatbots, VPN, and so forth [30]. Similarly, authors of [25], quantified the online COVID-19 information.

Succinctly, a cloud-based online production-enabling tool would increase the productivity of COVID-19 products. A few researchers [13] [28] [10] have suggested a cloud-enabled service model for production units. For instance, authors of [15] have developed a cloud-based integration of manufacturing units in order to enable a remote-access of the units; Martino et al. [6] have proposed a semantic representation for establishing Industry 4.0 based cloud services; Saivash et al. [26] have established a collaborative digital dentistry practicing platform using cloud manufacturing concepts, and so forth; Gajamohan et al. [17] have proposed a cloud-based robotics platform.

Besides, Prateek et al. [22] has proposed a computer vision-enabled approach to increase the social distancing pattern in the manufacturing location. However, not much research work applies the cloud-based services to develop COVID-19 products – i.e., very few research works have been discussed to improve the manufacturing aspects of COVID-19 preventive products.

3. RFCCPM Framework

This section explains the entities involved in the proposed RFCCPM framework, the RF-assisted Collaborative COVID-19 product manufacturing (RFCCPM) approach. In a nutshell, the RFCCPM framework allows manufacturers or smart city officials to quickly produce the demanding COVID-19 essentials, for example, preventive kits, depending on the status of locations in a cost-efficient manner. Figure 1 illustrates the entities of the framework.

3.1. RFCCPM Entities

The major entities involved in the collaborative production of COVID-19 products in a cost-efficient manner and their important functionalities are described below:

3.1.1. Information Collector

Information Collector is a cloud-based micro-service solution that collects the required status details of COVID-19 from smart city data repositories after the reception of appropriate permissions from them. A micro-service is a loosely-coupled tiny service that are independently deployable in clouds. In general, the number of COVID-19 patients, the number of deaths due to the virus, and the number of quarantined candidates are quite openly available in major cities of various countries as they are involved in reporting the infectious status to WHO. The *Information Collector* entity, a *golang* based cloud service, provides the information in a *csv* format to the RandomForest prediction engine after converting the formats of the source repository.

3.1.2. RF Prediction Engine

Predicting the number of quarantine cases in a particular location is mandatory to decide on manufacturing the number of COVID-19 preventive products. Smart city officials could utilize the data to fix policies and sketch layouts for a complete/partial lockdown in a location. Manufacturing preventive kits based

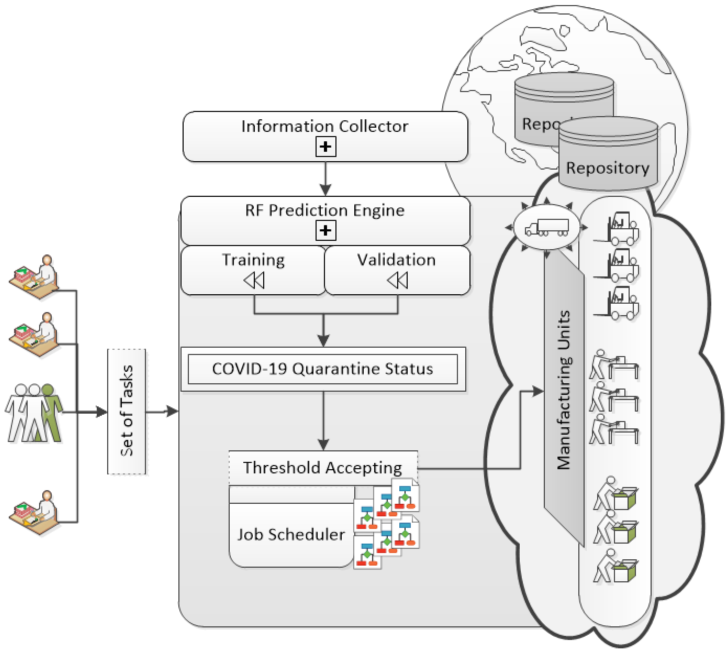


Figure 1: RFCCPM Framework

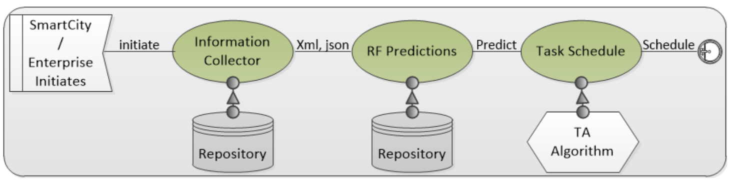


Figure 2: Processes Involved in the RFCCPM Framework

on the past information of the COVID-19 cases might not satisfy the requirements. Two issues are possible:

- A large volume of COVID-19 preventive kits may be required in a short period – i.e., the productions might get hampered due to the limited availability of employees during the period; or,
- Manufacturing a surplus amount of preventive kits leads to under-utilization.

The information is dynamic that the production depending on the current information would be a futile decision. Instead, RFCCPM utilizes a RandomForest-based prediction of COVID-19 cases for the future months so that the framework could proactively recommend the concerned for deciding on the production of the preventive kits. Besides, the RFCCPM enables a collaborated manufacturing platform that attains the manufacturing schedule with the limited number of employees during the raging pandemic period in a cost-efficient manner.

In general, the RF algorithm is a subset of AI and machine learning [9]; it is an ensemble-based learning algorithm. The *RF Prediction Engine* entity of RFCCPM incorporates the algorithm in order to train and predict the COVID-19 quarantine cases of a region. The training model is prepared from the information such as latitude, longitude, number of deaths, number of quarantined candidates, and so forth, for the locations where the preventive kits are required. The engine attempts to improve the prediction accuracy depending on the tuning parameters of the algorithm such as $mtry$ and the other variable selection methods. More detailed information about the algorithm is found in the previous literature [27].

3.1.3. Task Designer

Tasks such as manufacturing face masks, face shields, gloves, shoe covers, infrared thermometers, sanitizer, kit cover, and packaging them need to be formulated depending on the available manufacturing units within the reachable vicinity. The *Task Designer* entity of the framework attempts to pool tasks in a cloud database, namely, `mongodb` database. It considers several combinations of manufacturing options while designing tasks. The tasks are described in a machine-readable format such as XML, jade, or JSON.

The tasks included in the RFCCPM framework are classified into two broad categories: i) *Manufacturing* tasks and ii) *Packaging* tasks:

1. *Manufacturing COVID-19 Products*: Manufacturing COVID-19 preventive kits include manufacturing products such as face masks, face shields, gloves, hood caps, shoe covers, thermometers, sanitizers, and so forth. These products are often manufactured in different categories. For instances, i) face masks could be manufactured at different levels of protections – i.e., manufacturing face masks using N95 masks which provide higher protection from COVID-19 impacts or using cloths; ii) face shields may be manufactured using low-grade disposable plastics or poly-carbonates; iii) shoe covers could be fabricated using of non-woven materials or polypro pylene fabrics; and so forth. In addition to the COVID-19-related products, manufacturing the packing device that holds the preventive products is also considered as a task. The *Task Designer* entity of the RFCCPM framework prepares a set of optional combinations for manufacturing different COVID-19 products of preventive kits.
2. *Packaging Products*: Packaging is a task that needs to be accomplished by assembling all manufactured products into the packaging device.

3.1.4. Scheduler

Scheduler organizes tasks depending on the cost factors of allotting tasks to specific manufacturing units – i.e., it identifies the manufacturing tasks given the information about the available manufacturing units of a region/ location. Although the main objective of the *Scheduler* entity is to reduce the manufacturing cost, it has to consider several other parameters such as the availability of appropriate manufacturing units. For instance, if a face mask needs to be manufactured using N95, an appropriate manufacturing unit that is nearest to the vicinity should be available. Besides, it has to consider the prediction results available through the RF prediction engine. This is crucial as lockdown situations could hamper the transfer of products for the final preparation of predictive kits. *Threshold Accepting (TA)* [18] [27] scheduling algorithm is applied in the framework although several other scheduling algorithms could be implemented in the framework. The inner details of the cost-efficiency of the framework, while utilizing the *Scheduler* entity, is discussed in Section 4.

3.1.5. Processes

The following points highlight the crucial processes (see Figure 2) involved in the collaborative manufacturing of COVID-19 preventive kits from geo-distributed manufacturing locations considering the forecasting information of the *RF Prediction Engine*:

1. At *first*, a smart city authority or an enterprise initiates the interest to purchase preventive kits of COVID-19 in order to protect their residents or to sell them in shops of their jurisdiction.
2. *Second*, the *Information Collector* cloud service is invoked. The service gets access to the nearest COVID-19 data repository. The data is parsed, tidied, and formatted as per the requirement of the *RF Prediction Engine* of the framework.
3. *Third*, the tasks are finalized depending on the available manufacturing units that are accessible within the vicinity and the manufacturing options of different product categories.
4. *Fourth*, the quarantine information of different locations, where the accessible manufacturing units are located, is predicted using the *RF Prediction engine* of the framework. Thus, the scheduling of tasks to a particular location could be decided on considering the future issues of the virus – i.e., if the number of COVID-19 cases would be higher in a location/region, there is a high possibility of a requirement of more number of preventive COVID-19 kits. Thus, the production of products could be accordingly increased by rerouting manufacturing tasks to multiple manufacturing locations in a collaborative manner. Similarly, predicting the information could enable smart city officials or enterprises to quickly transport the required amount of preventive kits before the commencement of the "lockdown".
5. At *last*, an appropriate schedule of tasks depending on the number of available manufacturing units is prepared based on the TA algorithm. The scheduling aims at reducing the costs involved in the production of the entire COVID-19 preventive kits of a region.

4. Cost-Efficiency Mechanism

The cost-efficiency, while manufacturing the COVID-19 preventive kits, is tasked by the application of collaborative product manufacturing processes. Besides, the collaborative efforts are guided by the *Scheduler* entity of the RFCCPM framework. It applies TA algorithm for identifying a cost-efficient task schedule given the number of tasks and the product manufacturing units. This section explains the TA-based scheduling approach while preparing the schedule.

4.1. TA Scheduling Approach

TA of the RFCCPM framework initially collects the list of products P_i to be manufactured and the corresponding manufacturing sites M_s. The products are often expressed in different categories which are represented as $C_j \in P_i$. The production of an entire COVID-19 preventive kit is represented as a set of tasks. For example:

```
C2{P1}, C1{P2}, C3{P3}, C1{P4},
   C2{P5}, C1{P6}, C2{P7}, C2{P8}
                ---> Task Sets
MS3, MS2, MS7, MS10, MS11,
    MS9, MS4, MS1
```

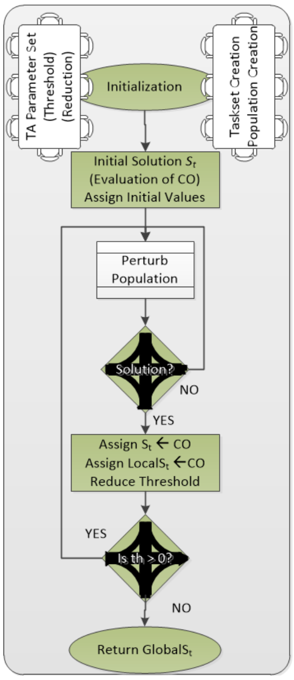


Figure 3: Threshold Accepting Scheduling Algorithm – Flowchart

where, C represents categories of P products. For instance, a face mask product manufactured using N95 in the manufacturing site $MS3$ is represented as C2{P1}–$MS3$; a face shield manufactured using polycarbonate in $MS2$ is represented as C2{P1}–$MS2$. A complete list of products and their categories is shown in Table 1. In the above task set, eight products are included.

Next, multiple sets of manufacturing tasks is formulated in one population PO of TA – i.e., each population set has collections of task sets S_t. Each manufacturing task set S_t, the preventive kit, consists of one category of the variety of products such as face mask, face shield, gloves, head cap, shoe cover, thermometer, sanitizer, and package. Besides, the initialization parameters that are required for the scheduling algorithm such as initial threshold, final threshold, threshold value, number of iterations, and the reduction step size of TA are assigned to the algorithm.

In the meantime, the costs involved ($Cost$) for manufacturing the individual category of products from various manufacturing sites Ms and their corresponding manufacturing time T_p are collected in the cloud-based `mongodb` database. In addition, the distance d_m between the manufacturing units of various locations is stored in the database.

Next, depending on the task set produced by the TA algorithm, the solutions are obtained for each manufacturing task set S_t – i.e., i) the cost TC_{ts} involved in the production of an entire COVID-19 preventive kit of a task set is calculated depending on the available manufacturing costs. Note that the products could be of different categories in the COVID-19 preventive kit; ii) similarly, the total manufacturing time TT_p of the task set is evaluated; and, the total distance Td_m involved for transporting the manufactured products between the manufacturing units in a task set is calculated. Depending on these values, the combined objective CO of a task set is calculated as shown in the equation 4.1.

$$CO = \sum(TC_{ts}, TT_p, Td_m) \qquad (1)$$

The CO of each task set S_t in a population set PO is evaluated in an iterative manner. However, only the best task set is stored in the database considering the minimal manufacturing costs of the production tasks. Once when the entire population set PO is evaluated, the local best task set $LocalS_t$ is recorded along with the obtained manufacturing time or costs. Next, the populations are perturbed with newer combinations and their corresponding CO of task sets S_t is recorded. The threshold value th of TA is reduced while increasing the populations. Whenever the obtained CO reaches the pre-assigned minimal CO value or whenever the threshold value th attains the final threshold value, the algorithm stops the further creation of iterations or evaluations. Finally, the global best task set $GlobalS_t$ is recorded based on the minimal CO values among the local task sets $LocalS_t$. The pictorial representation of the TA algorithm is shown in Figure 3.

Table 1
Categories of Products for COVID-19

Sl.No	Product	Type
1	MaskC1	Cloth-based
2	MaskC2	N95
3	MaskC3	Face printed
4	FshieldC1	Polycarbonate
5	FshieldC2	Disposable
6	FshieldC3	Kid Type
7	GloveC1	Latex Gloves
8	GloveC2	PVC Gloves
9	GloveC3	Plastic Gloves
10	HcapC1	Non-Woven
11	HcapC2	Cloth type
12	ScoverC1	Disposable
13	ScoverC2	Non Woven Type
14	ThermoC1	Fancy
15	ThermoC2	Wall mounted
16	SanitizerC1	Alcohol-based
17	SanitizerC2	herbal
18	PackageC1	Plastic
19	PackageC2	Leather

5. Experimental Results

This section manifests the importance of the RFCCPM framework. At first, the experimental setup is explained; next, the accuracy obtained due to the *RF Prediction engine* is revealed; and, at last, the identification of the manufacturing task schedule considering the availability of manufacturing units and the costs involved is disclosed using TA algorithm.

5.1. Experimental Setup

The experiments were carried out at a DELL precision tower 7810 machine of the IoT cloud research laboratory. The machine utilizes the 4.15.0-106-generic kernel Ubuntu version. The predictions were carried out by prediction algorithm written in R programming language version R4.0.0 and the services were written using `golang` version v1.14. The entire experiments were carried out considering the list of products and their categories illustrated in Table 1; Nineteen MSMEs of fourteen locations within one government agency of Kerala were utilized for calculating the manufacturing costs.

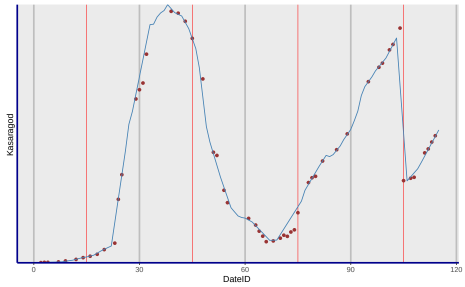
5.2. RF Predictions

In order to find the requirement for producing the number of COVID-19 preventive kits at the required prices or budget, predictions were undertaken to forecast the quarantine information of a particular location in the Kerala state of India. The datasets were collected from the COVID-19 repository of the Kerala government site [12]. It was modified with appropriate latitude and longitude information for the manufacturing locations of consideration. The datasets had values recorded from 1.3.2020 to 26.6.2020.

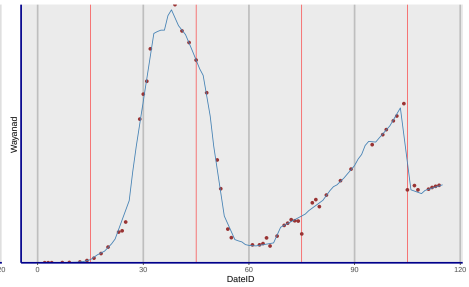
5.2.1. Validation Results

At first, the manifestation of utilizing the RF algorithm while predicting the possible number of quarantine candidates at a location was validated. To do so, fifty percent of the observations were utilized for creating a training model and the other fifty percent of the observations were tested using the RF algorithm.

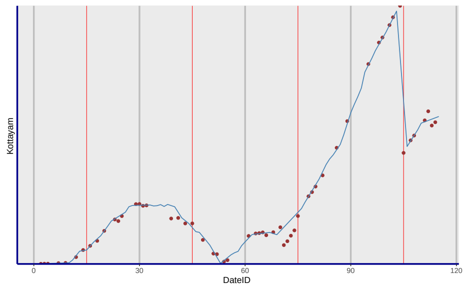
Figures 4 depicts on the training and the testing values of the number of quarantine candidates of four different manufacturing MSME



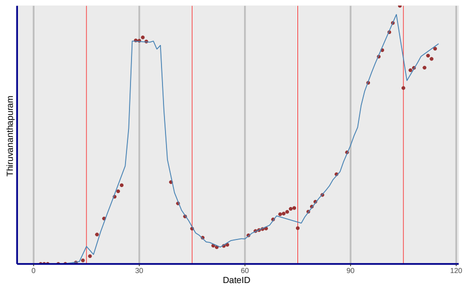
(a) Quarantine Cases in Kasaragod



(b) Quarantine Cases in Wayanad



(c) Quarantine Cases in Kottayam



(d) Quarantine Cases in Thiruvananthapuram

Figure 4: Validation Results of RF for Four Manufacturing Locations

locations, namely, Kasaragod, Wayanad, Kottayam, and Thiruvanthapuram. The y-axis of the Figures describes the number of quarantine cases for these locations. The x-axis discusses the increasing date of COVID-19 which is represented as unique identifiers.

The training values are represented in points and the tested values are shown in blue lines. It could be observed from the figures that the training and testing values are almost inclined to one another – i.e., the prediction accuracy is better for the experiment.

Hence, it is proven to utilize an RF algorithm for predicting the COVID-19 quarantine cases which relate to the number of required COVID-19 preventive kits in a city or a location of different geo-spatial monitoring points.

5.2.2. Accuracy Improvements

The prediction accuracy, which is measured as R^2 values, was evaluated to understand if further improvements are possible while tuning the algorithm-specific parameters. It was observed that there were a few possibilities such as including more number of variables while dividing at each tree node ($mtry$) to improve the prediction accuracy. Accordingly, experiments were held by increasing the number of variables for establishing the training models. Table 2 discloses the prediction accuracy values that were observed while conducting experiments with $mtry$=2, $mtry$=5, $mtry$=10, $mtry$=15, and $mtry$=20, for fourteen manufacturing locations of Kerala.

As seen in Table 2, it was inferred that the prediction improvement of over 5 percent is

Table 2
Prediction Accuracy Improvements in RF Algorithm

Sl.No	Location	mtry=2	mtry=5	mtry=10	mtry=15	mtry=20
1	Kasaragod	0.9459097	0.9733548	0.9774419	0.9796228	0.9796228
2	Kannur	0.9711467	0.9766201	0.9708988	0.9773691	0.9773691
3	Wayanad	0.9178817	0.9319097	0.9448657	0.9482104	0.9482104
4	Kozhikode	0.949926	0.9516512	0.9603881	0.9583597	0.9583597
5	Malappuram	0.9659479	0.9661579	0.96704	0.9681757	0.9681757
6	Palakkad	0.9541766	0.9570016	0.9545269	0.9490768	0.9490768
7	Thissur	0.9732814	0.9693427	0.9663719	0.9622127	0.9622127
8	Kochi	0.9260813	0.9397723	0.9371033	0.9331185	0.9331185
9	Idukki	0.9305873	0.9288297	0.935149	0.9213636	0.9213636
10	Kottayam	0.9479298	0.9635435	0.9720244	0.9841577	0.9841577
11	Alappuzha	0.9690321	0.9720363	0.977422	0.9779831	0.9779831
12	Pathanamthitta	0.9578222	0.9545819	0.9585167	0.957121	0.957121
13	Kollam	0.8263694	0.810251	0.7684122	0.7723276	0.7723276
14	Thiruvananthapuram	0.9043191	0.9008584	0.8888427	0.8484054	0.8484054

noticed in several locations – for instance, note the prediction accuracy observed in Thiruvananthapuram manufacturing station while improving $mtry$ values from 2 to 20; similar is the case with the other manufacturing locations such as Kollam, Kottayam, and Kasaragod.

Table 3
Number of Quarantine Cases in Kerala Districts

SlNo	Location	35^{th} Day
1	Kasaragod	433.52
2	Kannur	1196.2
3	Wayanad	394.02
4	Kozhikode	252.35
5	Malappuram	415.76
6	Palakkad	605.71
7	Thissur	291.02
8	Kochi	2470.02
9	Idukki	612.55
10	Kottayam	1540.22
11	Alappuzha	199.48
12	Pathanamthitta	147.6
13	Kollam	629.7
14	Thiruvananthapuram	1084.24

5.2.3. Prediction Results

Finalizing the algorithm-specific parameters to obtain higher accuracy – i.e., $mtry$=20 and number of trees $ntree$=100, predictions were achieved for the future. The obtained prediction results were illustrated in Table 3.

From Table 3, smart city officials or health department or the concerned officials could decide to instruct Micro-Small-Medium-Enterprises (MSMEs) for manufacturing COVID-19 preventive kits in a cost-efficient manner.

For example, the smart city officials of Thiruvanthapuram shall decide to procure 20 COVID-19 preventive kits for the thirty-fifth day based on the recommendations of the RFCCPM framework – i.e., a production of 20485 preventive kits has to be manufactured at a lower cost.

However, the recommendations about which manufacturing MSME needs to manufacture the products in a cost-efficient manner would be dependent on the TA algorithm of the framework. Besides, the TA parameters define the tuning of these recommendations in an elegant manner.

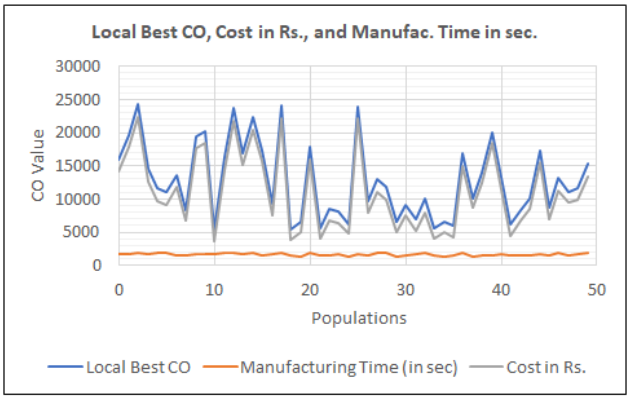


Figure 5: Local Best CO Obtained over 50 Populations

5.3. Manufacturing Jobs – Cost Efficiency

It is mandatory to tender works to different manufacturers depending on the quality and the cost involved in the production of the products. Questions such as i) Who needs to be offered the tender? Whether one manufacturer could handle manufacturing all products? This subsection identifies the job schedule that considers the cost-efficient manufacturing of products using the TA algorithm.

The following TA parameter settings were utilized while searching for the cost-efficient collaborative COVID-19 preventive kit manufacturing units or MSMEs:

```
Threshold = 0.0
Initial_Threshold = 0.099
Final_Threshold = 0
Threshold_Reduction = 0.001
Number of Iterations = 1000
Population Size = 50
```

The local best value $LocalS_t$ obtained for the experiments consisting of 50 populations with 1000 iterations of TA algorithm is shown in Figure 5.

The CO value is calculated using Eqn. 4.1. It could be observed that the local best CO value and the manufacturing cost identified for different sites vary for different populations – i.e., the algorithm searches for the MSMEs or manufacturing units that offer a minimal manufacturing cost. Even if a lower cost is identified in any one of the task set of a population, the task sets were perturbed in order to search for the best possible solution in the consecutive iterations or populations. In average, the manufacturing cost obtained among local best task sets $LocalS_t$ is Rs. 11013.

From the available local best values of task sets, the global best value $GlobalS_t$ is calculated by the TA algorithm. It is noticed that the minimal CO value is found as 5454; the minimal manufacturing cost is Rs.3734 for manufacturing one preventive COVID-19 kit; and, the manufacturing time is 1620 seconds. The task set that levied the global best result as per the TA algorithm $GlobalS_t$ is given below:

```
C3{P1}, C1{P2}, C2{P3}, C1{P4},
  C2{P5}, C1{P6}, C1{P7}, C1{P8}
MS7, MS3, MS5, MS13, MS10,
  MS4, MS4, MS3
```

As seen, the face mask of category 3 is scheduled for the manufacturing site $MS7$; face shield of category 2 is scheduled in $MS3$; hand gloves of category 3 is scheduled in $MS5$; hood cap of category 1 is scheduled in $MS13$; shoe cover of category 2 is allotted to $MS10$; thermometer of category 1 is scheduled in $MS4$; sanitizer of category 1 is allotted to $MS4$; and, the packaging of category 1 is scheduled in $MS3$. The detailed information of the categories of the products that are under consideration in this article is listed in Table 1.

The cost-efficiency of the identified global best task set $GlobalS_t$ when compared to the average manufacturing cost values of the local best results, which were identified from the population sets of the TA algorithm, is recorded as 66 percent.

6. Conclusion

The rapid dynamics of the COVID-19 pandemic has manifested the requirement of innovations in various sectors, including the manufacturing/fabrication sector. This article proposed an RFCCPM framework that combines the Random Forest and Threshold Accepting algorithm for enabling collaborative manufacturing of COVID-19 preventive kits in a cost-efficient manner. The framework was evaluated considering the COVID-19 quarantine information and MSME enterprises of fourteen manufacturing locations in Kerala, India. The necessity of the RFCCPM framework was manifested through experiments that revealed a cost efficiency of 66 percent for the identified job schedule.

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