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Application of a Cold-Chain Logistics Distribution System Based on Cloud Computing and Web Delivery Date Management

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ABSTRACT

The cold chain maintains and transports fresh food in the correct temperature range for slow biological decay processes and delivers safe, high-quality food to customers. Ensuring that quality and efficiency are not affected by the supply chain of cold chain products is a goal. Therefore, this paper proposes the intelligent time scheduling management model (ITSMM) based on cloud computing and a web-based platform for cold-chain logistics and distribution systems. This paper establishes a time scheduling model to reduce the overall order operation cost, diminish the variance among the expected and actual time of finalizing the service orders, and improve useful logistics service providers' satisfaction. Data, including all cold chain phases (distributors, industry, consumers, and retailers), have been gathered. This paper examines the distribution cost and time refrigerated vehicles, thus instituting a cold chain distribution vehicle path optimization.

KEYWORDS

Cold-Chain, Deliver Schedule Management, Distribution System, Logistics

INTRODUCTION

The size of the cold chain logistics has recently been shown to grow at a rapid rate of approximately 15 percent each year.The main issue faced by these systems is carbon emission during transportation. The carbon emission due to transportation amounts to around 14% of total carbon emissions. Hence, systems that minimise carbon emission are a major task in cold chain logistics (Liu et al., 2020). Fresh food cannot be transported at room temperature. During transportation, they must be maintained at a suitable low temperature so that the food remains in its original state. Thus,the cold chain logistics system maintains an appropriate temperature for food materials like ice cream, fresh fruits, pharmaceutical medicines,etc. (Chen, 2020).

These cold chain logistic systems employ various sectors like warehouses, transportation units, repacking units, transportation units etc (Poornima, 2020). Food safety is a crucial task, especially

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in the case of medicines. The required low temperature is not maintained; the medicines may lose their quality, leading to serious disasters (Chen et al., 2020). Besides, dairy products such as milk may easily lose their original form when the temperature gets high. To enable the customers to get complete satisfaction, the warehouses and the transportation units must be equipped with suitable freezing units. With the rapid increase in internet technologies usage, all these units are equipped with IoT units (Wang et al., 2020).

These units are used for the collection of real-time data. It helps in the identification of a suitable path to reach the customers (Poornima & Arulselvi, 2020). The identification of the path is done based on the monitoring of traffic. It helps the transportation units to reach the customers on time (Qi and Hu, 2020). Big data analytics and cloud computing technologies are popularly integrated with the cold chain logistics systems to enable the products' fast delivery. The dynamic information such as the travel route, the current storage status, vehicle details is constantly updated in the cloud (Song et al., 2020).

Itenables customers to monitor their status through smart devices.The establishment of the path with minimum cost is done through various optimization algorithms (Arulselvi & Poornima, 2020). Genetic algorithms are widely employed for solving the optimization problem. Minimization of usage of network bandwidth is another important criterion in cold chain logistics (Wang & Wen, 2020). Besides, improvement of quality of service is another major objective. The customer satisfaction index, reduction in carbon emissions, the establishment of the shortest path, minimization of storage levels, decreasing the latency of computation are other factors that determine the efficiency of the cold chain logistic systems (Peng et al., 2020).

It has been found through a survey that, among various food products being transported, around 40% of the products required refrigeration facilities during transportation (Joshua Jeyasekar et al., 2019). Furthermore, these refrigeration units consume approximately 53% of the power supply. Thus minimization of power supply requirements is a major task (Dai et al., 2020). Vehicle route problem (VRP) is the technique employed in optimising the route used for the transportation of these products. It has two main objectives. The first objective is the minimization of transportation cost. Here the second objective is the minimization of transportation distance (Hu et al., 2020).

Based on the introduction on cold chain logistics, a new delivery schedule management scheme is proposed in this research.

The contributions of the paper are followed as

- A novel model called Intelligent Time Scheduling Management Model (ITSMM) based on cloud computing is proposed.
- The components of cold chain logistics are discussed.
- The delivery schedule management for cold chain logistics is analyzed.
- The proposed ITSMM model is compared with standard algorithms like Dijkstra's algorithm (DKST), the shortest remaining time first algorithm (SRTF), and the shortest seek time first algorithm (SKTF).

The remainder of the study is followed as section 1, and section 2 discussed the introduction and existing chain logistics models. In section 3, Intelligent Time Scheduling Management Model (ITSMM) has been suggested. The numerical results were carried out in section 4. The research article ends in section 5.

RELATED WORK

Qin et al., (2020) have presented a technique for solving the vehicle routing optimization problem. This scheme is proposed based on the carbon trading mechanism. The carbon trading mechanism was opted to reduce the carbon emission cost. Further, the other objective was to improve the satisfaction rate of the customers. Zhang et al., (2019) have utilized the ant colony optimization algorithm for the cold chain logistics framework. This paper introduced the ribonucleic acid technique for the optimization of cost. The objective was to create an economy with low carbon content. The optimization function was framed such that the low-temperature transportation was enhanced.

Kuo et al., (2010) have introduced a new technique based on the joint distribution system for cold chain logistics. This technique used temperature control units to ensure the quality of the food products transported.The objectives were to establish timely deliveries at minimal cost and minimal carbon emissions. Wei et al., (2019) have proposed a system for transporting agricultural products using a cold chain. The IoT framework was integrated with the cold chain systems to establish real-time tracking of information. To ensure the freshness of the agricultural products, real-time supervision was done using cloud computing techniques.

Li et al., (2019) has utilized the particle swarm optimization technique to identifyan optimal path. A new model called the green vehicle routing model was proposed. The objectives of this model included cost minimization, freshness assurance and lesser penalty cost. The mathematical model was designed to support routing problems. Li et al., (2019) has introduced a context-aware framework for the cold chain distribution. It involves the risk management system for the computation of logistics distribution. The traceability of cargo load is done using the internet of things framework. These IoT devices capture the data and transmit them to the cloud unit. Liao et al., (2019) has proposed a new optimization model, considering the constraint of carbon emission. The economic cost and transportation cost was minimized in this framework. Hard time window was employed for the optimization of distribution cost.

Qiao et al., (2019) has used modern biotechnology for agricultural products of china were used for the analysis. The temperature and damage cost was evaluated and optimized using biotechnology. Bai et al., (2019) have implemented nanotechnology to store fresh food in cold chain logistics. Chemical coolants were used in the preservation of food materials. The transportation was done using ice bag controllers. Wei et al., (2019) presented a scheme for the cold chain distribution of agricultural products. Different distribution models were analysed and evaluated for the selection of the best mode using cloud computing techniques.

Li et al., (2021) The cold chain articles are tracked in real time by using the Internet of Things and the data are recorded and realised using the GPS system. WSM is implemented with the integration of FPGA Xilinx software wireless controller. The scaling impact under integer optimization and the total economic advantages of transport continue to maximise the evidence of trunk transit on goods passing through the button point. A special reference is provided by the cold chain logistics in the transportation decision makers' network design. It is supposed to be based on the suggested architecture of PDTT and an improved IoT data model.

Xiong, H et al., (2021) The standard optimization strategy takes a great deal of time to search for the world-leading way to locate it, leading to greater distribution costs and reduced efficiency. A cold logistics distribution path optimization method has been created to handle the above listed challenges based on an improved ant-colonies optimization algorithm (IACO). Specially, the unified IACO may have additional restrictions, such as the factor of transport time, the factor of transport cooling and the factor of mean road patency.

Based on the above research, a time scheduling model has been developed to reduce the overall order operation cost and improve customer satisfaction.

PROPOSED METHODOLOGY

Components of Cold Chain Logistics

The second component is cold storage utilised between the shipping process for food storage systems. There must be no leaking in the food packaging and the low temperature must be maintained constantly. An intelligent transport system is employed to construct a path between the manufacturer and the customer with the shortest distance and the shortest time.

Cold chain logistics systems frequently blend big data modelling and cloud computing technology to facilitate quick supplies of items. The cloud continually updates dynamic information, such journey route, current storage status, vehicle specifics.

This framework involves the integration of a supply chain with the temperature control unit. It is used for the safe transportation of products that needs low temperature for preservation.

Figure 1 illustrates the components of cold chain logistics. The first component is freshness management. This unit is responsible for maintaining the freshness of the food being transported. It is crucial, especially in the case of pharmaceutical medicines. Here the second component is cold storage. The food is stored using cold storage systems between the transportation process. It is becausethe distance between the manufacturer, and the customer is large. The package is another important component. The food package must be done such that there is no leakage, and the low temperature is maintained at a constant level. An intelligent transport system is used for establishing the path with the shortest distance and shortest time between the manufacturer and the customer. Warehouses are used for the temporary storage of food commodities. Refrigerated vehicles are used to ensure the freshness of food during travel. It is important, especially in the case of commodities like ice cream, medicines, etc.

The low temperature necessary here is well maintained, as well as medicine that might improves its quality, resulting in optimized outcomes. The warehouses and the transportation units should be supplied with appropriate freezing equipment to enable consumers to be completely satisfied. The second component is cold storage utilised between the shipping process for food storage systems. There must be no leaking in the food packaging and the low temperature must be maintained constantly. An intelligent transport system is employed to construct a path between the manufacturer and the customer with the shortest distance and the shortest time.

Cold Chain Logistics Distribution System

The cold chain logistics distribution system comprises two main levels. These two levels split the entire transport system into two sectors.

Figure 1. Cold Chain Logistics Components

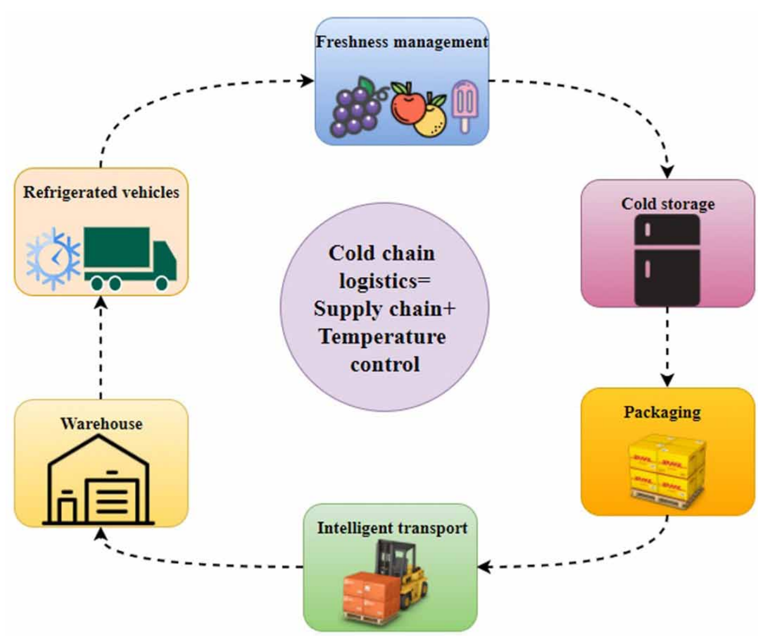


Figure 2 shows the model of the cold chain logistics distribution system.Therefore this system involves the manufacturer, level-1 transport, storage, level-2 transport and the customer unit.The level-1 sector comprises the manufacturer, level-1 transport and storage. Here in this unit involves the transfer of data from the manufacturing industry to the temporary storage unit. The second sector comprises the storage unit, level-2 transport and the customer unit.

Delivery Schedule Management for Cold Chain Logistics

The deliver schedule management system for cold chain logistics is used to find the best route between the manufacturer and the customer using suitable software tools.

Figure 3 illustrates the model of deliveringa schedule management system. In this model, find multiple paths between the manufacturer and the delivery sector. Thus, the management system is used for computing the path that has the minimum latency and length. From Figure 3 infer that there are multiple transport routes to reach the warehouse. Thus from the warehouse, the food is given to the repacking unit. From the repacking unit, the food is transferred to the distributed. Finally, the food reaches a specific destination, including hospitals, direct customers, pharmacy, shops, etc.

Figure 2. Distribution System Model

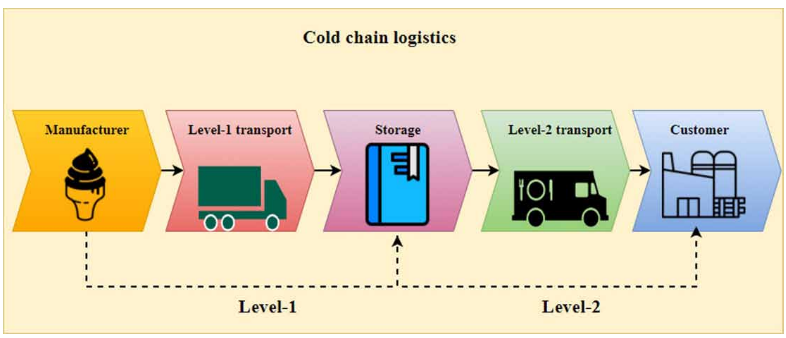
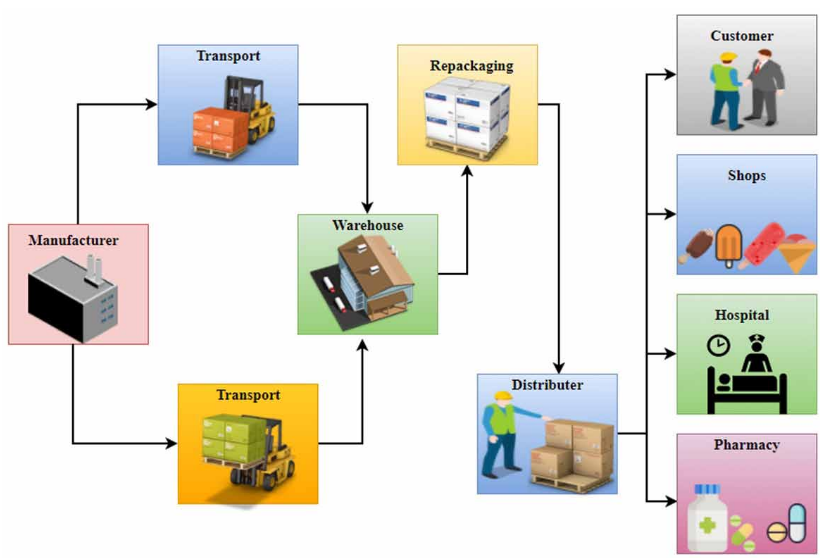


Figure 3. Schedule Management System Model



- The new ITSMM, which is based on cloud computing, is suggested in which the cold chain logistics components will be covered.
- An analysis of the delivery timetable for the logistics of the cold chain.

Proposed Intelligent Time Scheduling Management Model (ITSMM)

The intelligent schedule management model is the software algorithm used for the computation of path with the shortest length and time. It is very important to maintain the freshness of the food and to deliver the food on time. The variance between the expected and the actual time can be minimized using this ITSMM algorithm.

Figure 4 shows the proposed intelligent schedule management model. This model comprises multiple paths for the food to reach the customer from the manufacturer. The entire model has linked with the Internet of Things (IoT) framework using the cloud module. The whole path is given to the cloud. Using cloud computing, the shortest distance is computed based on real-time traffic data. The cloud computes and identifies the ideal path and provides an output using the proposed algorithm. Based on the computed path, the food is transported.

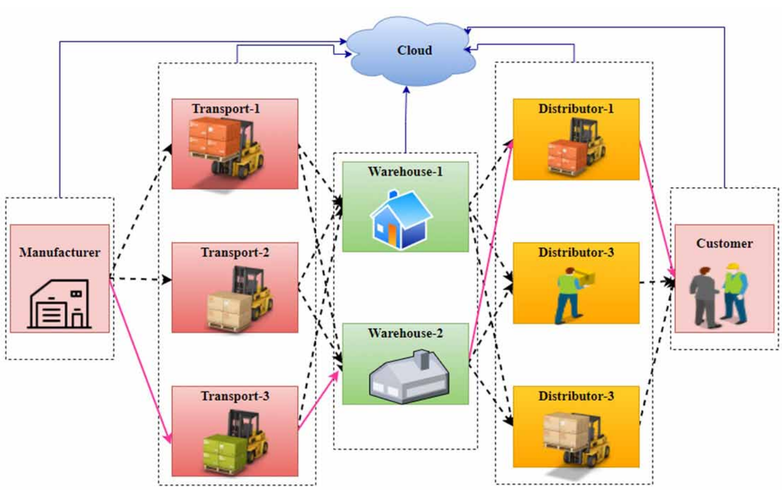
Intelligent Time Scheduling Management (ITSM) algorithm is done based on various input parameters. These include a list of paths $P = \left\{p_{i,j}\right\} \forall i = 1:N, j = 1:M$, list of cost $C = \left\{c_{i,j}\right\} \forall i = 1:N, j = 1:M$, list of distance $D = \left\{d_{i,j}\right\} \forall i = 1:N, j = 1:M$, list of traffic $T = \left\{t_{i,j}\right\} \forall i = 1:N, j = 1:M$, time latency delay $L = \left\{l_{i,j}\right\} \forall i = 1:N, j = 1:M$, transportation level $T = \left\{t_{i,j}\right\} \forall i = 1:N, j = 1:M$, and satisfaction levels $S = \left\{s_{i,j}\right\} \forall i = 1:N, j = 1:M$.

The transportation cost is computed as

$$TC\left(i,j\right) = \left(c_{i,j} * d_{i,j}\right) - \left\{\sum_{i=1}^{M} p_{i,j} + \sum_{i=1}^{M} T_{i,j}\right\} \tag{1}$$

As inferred from equation (1) $TC\left(i,j\right)$ refers to the transportation cost, *i* and *j* are the route along x and y direction, $c_{i,j}$ is the cost metric, $d_{i,j}$ is the distance metric, $p_{i,j}$ is the path indicator,

Figure 4. Intelligent Schedule Management Model



$\sum_{i=1}^{M} p_{i,j}$ is the total summation of the path indicator for all the paths, $t_{i,j}$ indicates the transportation level and $\sum_{i=1}^{M} t_{i,j}$ is the total summation of the transportation levels for all the paths.

The energy cost of vehicles is calculated using

$$EC\left(i,j\right) = TC\left(i,j\right) + \frac{t_{i,j} * \exp(s_{i,j})}{\exp(l_{i,j})} + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{M} c_{i,j}\right] \tag{2}$$

As found from equation (2) $EC\left(i,j\right)$ is the energy cost of vehicles $TC\left(i,j\right)$ refers to the transportation cost, $t_{i,j}$ indicates the transportation level, $s_{i,j}$ is the satisfaction level, $\exp(s_{i,j})$ is the exponential satisfaction level, $l_{i,j}$ suggests the time latency delay, $\exp(l_{i,j})$ is the exponential latency level and $c_{i,j}$ is the cost metric.

The penalty cost is given by

$$PC\left(i,j\right) = \left[\left[\sum_{i=1}^{N}\sum_{j=1}^{M} l_{i,j}\right] / \left[\sum_{i=1}^{N}\sum_{j=1}^{M} t_{i,j}\right]\right] * \exp(s_{i,j}) \tag{3}$$

Where $PC\left(i,j\right)$ indicates the penalty cost, $l_{i,j}$ suggests the time latency delay, $\left[\sum_{i=1}^{N}\sum_{j=1}^{M} l_{i,j}\right]$ $t_{i,j}$ shows the transportation level, $\sum_{i=1}^{N}\sum_{j=1}^{M} t_{i,j}$ is the total summation of the transportation levels for all the paths, $s_{i,j}$ is the satisfaction level and $\exp(s_{i,j})$ is the exponential satisfaction level.

The food processing cost is calculated as

$$FC\left(i,j\right) = p_{i,j} * \left[\left(l_{i,j} - \lambda\right)\right] * \prod_{i=1}^{M} d_{i,j} \tag{4}$$

As defined from equation (4) $FC\left(i,j\right)$ is the food processing cost $p_{i,j}$ is the path indicator, $l_{i,j}$ indicates the time latency delay, λ is the weighting factor, $\left[\left(l_{i,j} - \lambda\right)\right]$ is the difference between the time latency delay and weighting factor, and $d_{i,j}$ is the distance metric.

The cloud computing cost is given by

$$CC\left(i,j\right) = \left[PC - s_{i,j2}^{\,2} - FC - p_{i,j2}^{\,2}\right] \tag{5}$$

As shown from the above equation (5) $CC\left(i,j\right)$ is the cloud computing cost, PC indicates the penalty cost, $s_{i,j}$ is the satisfaction level, FC is the food processing cost, $p_{i,j}$ is the path indicator, $PC - s_{i,j2}^{\,2}$ is the l_2 norm of the difference between the penalty cost and the satisfaction level and $FC - p_{i,j2}^{\,2}$ is the l_2 norm of the difference between the food processing cost and the path indicator.

The repackaging cost is calculated using

$$RC\left(i,j\right)=\left\{\sum_{i=1}^{M}\frac{CC-\exp(p_{i,j})}{FC-\exp(c_{i,j})}\right\}/\left\{\sum_{i=1}^{M}\frac{PC-\exp(p_{i,j})}{EC-\exp(c_{i,j})}\right\} \tag{6}$$

$RC\left(i,j\right)$ denotes the repackaging cost, CC is the cloud computing cost, $p_{i,j}$ is the path indicator, $c_{i,j}$ is the cost metric, FC is the food processing cost, PC indicates the penalty cost and EC is the vehicle's energy cost.

The path selection cost is given as

$$PS(i,j)=[d_{i,j}+t_{i,j}]/\left[\arg\min_{i,j} RC(i,j)\right] \tag{7}$$

As described from the above equation (7) $PS\left(i,j\right)$ is the path selection cost $d_{i,j}$ is the distance metric, $t_{i,j}$ indicates the transportation level, $RC\left(i,j\right)$ denotes the repackaging cost and $d_{i,j}+t_{i,j}$ is the sum of the distance metric and transportation level.

The distance metric is computed as

$$DM(i,j)=[s_{i,j}+l_{i,j}]/\left[\arg\max_{i,j} PS(i,j)\right] \tag{8}$$

As explored in equation (8) $DM\left(i,j\right)$ is the distance metric $s_{i,j}$ is the satisfaction level, $l_{i,j}$ indicates the time latency delay, $\left[s_{i,j}+l_{i,j}\right]$ is the sum of the satisfaction level and the time latency delay, $PS\left(i,j\right)$ is the path selection cost and $\arg\max_{i,j} PS(i,j)$ gives the values of *i* and *j* that gives maximum values of path selection cost.

The latency metric is given by

$$LM\left(i,j\right)=\left[PS\left(i,j\right)\cup DM\left(i,j\right)\right]/\left[FC\left(i,j\right)\cap CC\left(i,j\right)\right] \tag{9}$$

As denoted in equation (9) $LM\left(i,j\right)$ is the latency metric, $PS\left(i,j\right)$ is the path selection cost, $DM\left(i,j\right)$ is the distance metric, $FC\left(i,j\right)$ is the food processing cost and $CC\left(i,j\right)$ is the cloud computing cost.

Finally, the ITSM metric is computed as

$$ITSM=\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}\left[TC\left(i,j\right)+EC\left(i,j\right)+PC\left(i,j\right)\right]/\left[FC\left(i,j\right)+CC\left(i,j\right)+RC\left(i,j\right)\right]}{PS\left(i,j\right)-LM\left(i,j\right)} \tag{10}$$

As each state observation in equation (10) $TC\left(i,j\right)$ refers to the transportation cost, $EC\left(i,j\right)$ is the energy cost of vehicles, $PC\left(i,j\right)$ indicates the penalty cost, $FC\left(i,j\right)$ is the food processing cost, $CC\left(i,j\right)$ is the cloud computing cost, $RC\left(i,j\right)$ denotes the repackaging cost and $LM\left(i,j\right)$ is the latency metric and $PS\left(i,j\right)$ is the path selection cost.

The path diagram for the proposed ITSM derivation is shown in Figure 5.

Figure 5 shows the path diagram of the proposed CCDI computation. This figure $TC\left(i,j\right)$ refers to the transportation cost, $EC\left(i,j\right)$ is the energy cost of vehicles, $PC\left(i,j\right)$ indicates the penalty cost, $FC\left(i,j\right)$ is the food processing cost, $CC\left(i,j\right)$ is the cloud computing cost, $RC\left(i,j\right)$ denotes the repackaging cost, $LM\left(i,j\right)$ is the latency metric and $PS\left(i,j\right)$ is the path selection cost.

Advantages of the Proposed Scheme

The proposed scheme's main advantage is reducing the difference between the actual and the expected time. The second advantage is service provider satisfaction. The third main advantage is the increase in the effectiveness of enterprise management.

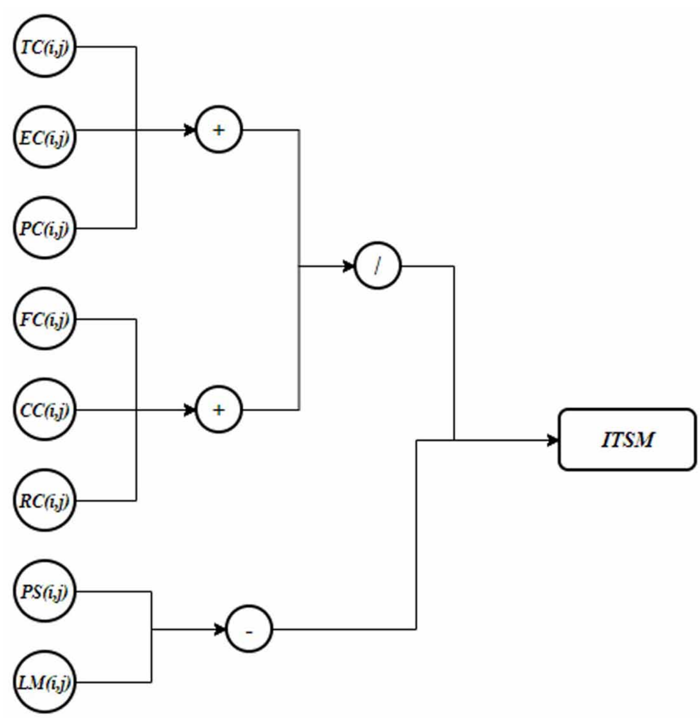
RESULTS AND DISCUSSION

The proposed ITSMM model's numerical results have been executed based on the metrics Performance Analysis, cost efficiency,low operational cost factor, minimum time variance, and overall performance.

Performance Analysis

For quantitative evaluation metrics like operational cost factor, time variance factor, service provider satisfaction rate, distribution cost efficiency, product stability rate, intelligent storage index, cold chain

Figure 5. CCDI Computation Path Diagram



index, transport integrity factor and conditional demand rate. Comparison of the proposed ITSMM model is done using standard algorithms like Dijkstra's algorithm (DKST), shortest remaining time first algorithm (SRTF), and the shortest seek time first algorithm (SKTF). The analysis is done for the cold logistics transport of ten different products.

Table 1 shows acomparison of the operational cost factor. It refers to the total operating cost involved in the cold chain logistics model. The average cost factor for Dijkstra's algorithm is found to be 0.551, the average cost for the shortest remaining time first algorithm is computed as 0.563, and the average cost for the shortest seek time first algorithm is found to be 0.502. However, the proposed ITSMM scheme achieves a minimum cost of 0.159. Thus, the proposed ITSMM scheme's cost is the least due to identifyinga minimum latency path.

Table 2 shows a comparison of the time variance factor. This factor refers to the difference between the variance between the expected and the actual time. The SSTF scheme attains the maximum time variance of 0.615. Therefore DKST attained the next lowest time variance with a value of 0.558. SRTF

Table 1. Comparison of the Operational Cost Factor

Product	The overall operational cost factor			
	DKST	SRTF	SSTF	ITSMM
1	0.6	0.67	0.51	0.16
2	0.41	0.47	0.45	0.18
3	0.49	0.59	0.38	0.15
4	0.59	0.35	0.39	0.12
5	0.42	0.76	0.51	0.18
6	0.44	0.74	0.34	0.11
7	0.61	0.71	0.6	0.12
8	0.43	0.43	0.54	0.21
9	0.72	0.6	0.65	0.23
10	0.8	0.31	0.65	0.13

Table 2. Comparison of time variance factor

Product	Time variance factor			
	DKST	SRTF	SSTF	ITSMM
1	0.62	0.57	0.52	0.21
2	0.31	0.46	0.56	0.26
3	0.33	0.35	0.53	0.36
4	0.46	0.61	0.74	0.18
5	0.57	0.69	0.56	0.11
6	0.63	0.51	0.78	0.09
7	0.5	0.34	0.62	0.06
8	0.71	0.43	0.78	0.18
9	0.66	0.37	0.42	0.12
10	0.79	0.44	0.64	0.17

attains a time variance of 0.477. The proposed ITSMM achieves a time variance of 0.174. Thus, the difference between the expected and actual time variance is minimum for the proposed scheme due to the traffic data's real-time tracking.

Table 3 shows the comparison of service provider satisfaction rate. The proposed ITSMM scheme has an average satisfaction rate of 87.85%. However, other schemes like Dijkstra's algorithm, the shortest remaining time first algorithm and the shortest seek time first algorithm attain a low satisfaction rate of 51.92%, 55.69% and 57.11%, respectively. In this way, the satisfaction of the service provider is maximum for the proposed scheme.

Table 4 shows a comparison of distribution cost efficiency. It refers to the total efficiency in the cost distribution in the cold chain. The mean distribution cost efficiency for Dijkstra's algorithm is found to be 57.62%; the mean distribution cost efficiency for the shortest remaining time first algorithm is computed as 56.95%.And the mean distribution cost efficiency for the shortest seeksto time the first algorithm is 54.27%. However, the proposed ITSMM scheme achieves a mean distribution cost

Table 3. Comparison of service provider satisfaction rate (%)

Product	Service provider satisfaction rate (%)			
	DKST	SRTF	SSTF	ITSMM
1	44.83	54.43	63.96	98.6
2	45.94	58.93	49.77	93.54
3	51.21	41.86	48.37	89.51
4	55.39	52.94	79.4	88.95
5	34.27	78.16	31.88	81.13
6	43.12	57.34	74.26	92.96
7	70.05	56.06	75.67	80.8
8	31.46	41.58	69.81	81.35
9	76.45	54.44	34.93	89.91
10	66.52	61.2	43.09	81.83

Table 4. Comparison of distribution cost efficiency (%)

Product	Distribution cost efficiency (%)			
	DKST	SRTF	SSTF	ITSMM
1	46.77	74.55	60.88	95.55
2	63.99	46.71	72.98	95.54
3	36.82	64.94	70.28	93.73
4	66.06	39.89	58.84	82.84
5	35.33	31.52	39.14	92.53
6	62.69	67.21	41.99	89.85
7	54.71	55	74.33	98.49
8	68.96	54	31.43	92.33
9	65.75	75.24	54.49	95.21
10	75.19	60.49	38.39	88.62

efficiency of 92.46%. Therefore, the mean distribution cost efficiency for the proposed ITSMM scheme is the best due to penalty cost.

Figure 6 shows the variation of product stability rate; the product stability rate gives the product's stability during the transport. DKST attains an average product stability rate of 55.3%.SRTF achieves a rate of 54.8%. Similarly, SSTF reaches a rate of 60.9%. However, the proposed ITSMM attains the highest stability rate of 87.6%. Thus, the products' stability in maximum with the proposed scheme since the food processing cost is added to the ITSM computation.

Figure 7 shows the variation of the intelligent storage index. Since the proposed scheme uses an intelligent storage system during its products, its intelligent storage index value is maximum. It has the highest value of 0.919. The DKST has an intelligent storage index of 0.58, SRTF has an intelligent storage index of 0.48, and SSTF has an intelligent storage index of 0.548. Thus, it is evident that the proposed scheme is the best in terms of intelligent storage index.

Figure 8 shows the variation of the cold chain index. The cold chain index gives the reliability of the product during cold chain transport. Here the DKST attains an average cold chain index of 0.505. SRTF attains a cold chain index of 0.485. Similarly, SSTF attains a cold chain index of 0.508. However, the proposed ITSMM attains the highest cold chain index of 0.916. Thus, the products' reliability in maximum with the proposed scheme due to the incorporation of repackaging cost.

Figure 9 shows the variation of the transport integrity factor. ITSMM achieves the highest aspect of 0.9,which is close to 1. Thus, the integrity of the proposed scheme is the highest. The next highest is attained by SSTF with a rate of 0.615, followed by SRTF with a rate of 0.561. The DKST scheme has the least value of 0.557. Thus, the integrity of ITSMM is almost equal to unity.

Figure 6. Product Stability Rate Variation

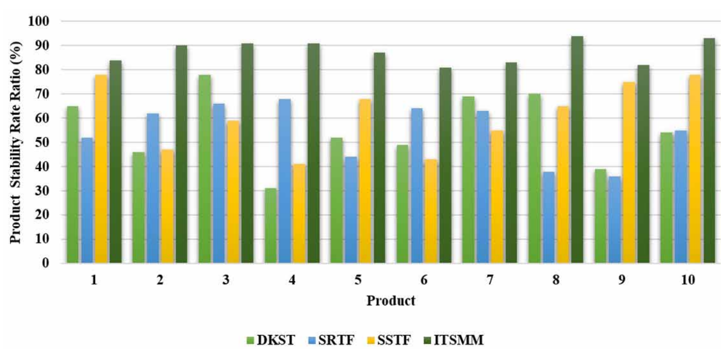


Figure 7. Intelligent Storage Index Variation

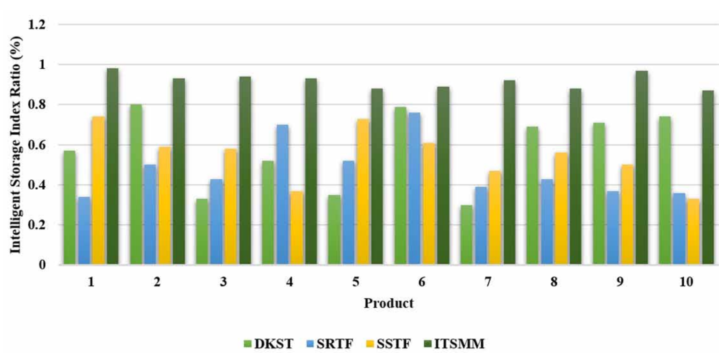


Figure 8. Cold Chain Index Variation

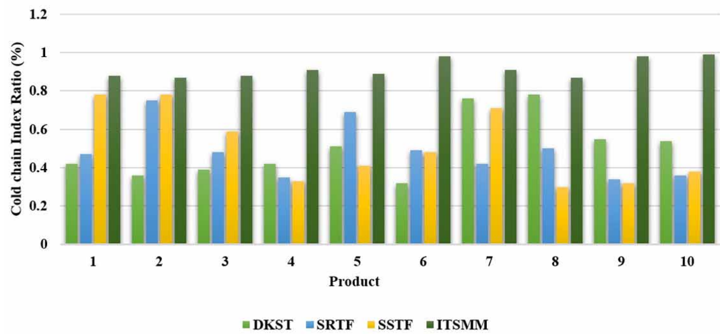


Figure 9. Transport Integrity Factor Variation

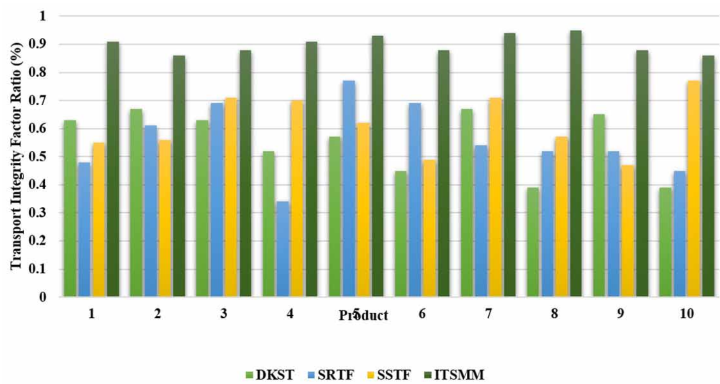
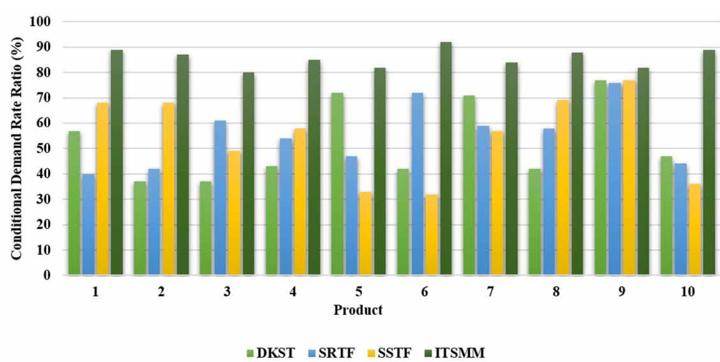


Figure 10 shows the comparison of conditional demand rate. It refers to the total demand for the products in the cold chain. The mean conditional demand rate for Dijkstra's algorithm is found to be 52.5%; the mean conditional demand ratefor the shortest remaining time first algorithm is computed as 55.3%.And the mean conditional demand ratefor the shortest seeksto time the first algorithm is 54.7%. However, the proposed ITSMM scheme achieves a mean conditional demand rateof 85.8%.

Figure 10. Comparison of Conditional Demand Rate



Therefore, the mean conditional demand ratefor the proposed ITSMM scheme is the best due to the efficient route computation technique.

Therefore the proposed model generated a high average satisfaction rate of 87.85%, high average cost efficiency of distribution of 92.46%, a low operational cost of 0.159 and a minimum time variance of 0.174 compared with existing methods.

CONCLUSION

This researchproposed a new model called the Intelligent Time Scheduling Management Model (ITSMM). This model is used for the computation of the path with the shortest length and time to ensure the freshness of the food and deliver the food on time.The entire framework is linked with the Internet of Things (IoT) system using the cloud module. This module is used for the tracking of real-time traffic to ensure the selection of the optimal path. The proposed cold chain distribution-based vehicle path optimizationschemeis designed to maintain the quality of the food being transported. The proposed scheme is compared using standard algorithms like Dijkstra's algorithm (DKST), the shortest remaining time first algorithm (SRTF), and the shortest seek time first algorithm (SKTF). For quantitative evaluation of the proposed ITSMM model, metrics like operational cost factor, time variance factor, service provider satisfaction rate, distribution cost efficiency, product stability rate; intelligent storage index, cold chain index, transport integrity factor and conditional demand rate were employed. It is inferred that the proposed model produceda high average satisfaction rate of 87.85%, high mean distribution cost efficiency of 92.46%, a low operational cost factor of 0.159 and a minimum time variance of 0.174.

REFERENCES

Arulselvi, G., & Poornima, D. (2020). Implementation of Precision Soil and Water Conservation Agriculture (PSWCA) through Machine Learning, Cloud Enabled IoT Integration and Wireless Sensor Network. European Journal of Molecular & Clinical Medicine, 7(3), 5426-5446, doi: doi:10.1016/j.rinp.2019.01.083

Bai, B., Zhao, K., & Li, X. (2019). Application research of nano-storage materials in cold chain logistics of e-commerce fresh agricultural products. Results in Physics, 13, 102049. 10.1016/j.rinp.2019.01.083

Chen, J., Xu, S., Chen, H., Zhao, C., & Xue, K. 2020, May. Research on optimization of food cold chain logistics distribution route based on internet of things. In Journal of Physics: Conference Series (Vol. 1544, No. 1, p. 012086). IOP Publishing, doi:10.1088/1742-6596/1544/1/012086

Chen, Y. H. (2020). Intelligent Algorithms for Cold Chain Logistics Distribution Optimization based on Big Data Cloud Computing Analysis. *Journal of Cloud Computing*, *9*(1), 1–12. doi:10.1186/s13677-020-00174-x

Dai, J., Che, W., Lim, J. J., & Shou, Y. (2020). Service innovation of cold chain logistics service providers: A multiple-case study in China. *Industrial Marketing Management*, *89*, 143–156. doi:10.1016/j.indmarman.2019.08.002

Hu, L., Xiang, C., & Qi, C. 2020, March. Cold-Chain Logistics Distribution Routing Optimization Based on PSO. In IOP Conference Series: Materials Science and Engineering (Vol. 790, No. 1, p. 012166). IOP Publishing. doi:10.1088/1757-899X/790/1/012166

Jeyasekar, D., Arulselvi, G., Vedanarayanan, V., & Poornima, D., 2019. Bone Cancer Identification and Classification Using Hybrid Fuzzy Clustering With Deep Learning Classification. *Journal of Advanced Research in Dynamical and Control Systems, 11*(Spl10), pp.88–98, .10.5373/JARDCS/V11SP10/20192779

Kuo, J. C., & Chen, M. C. (2010). Developing an advanced multi-temperature joint distribution system for the food cold chain. *Food Control*, *21*(4), 559–566. doi:10.1016/j.foodcont.2009.08.007

Li, G. (2021). Development of cold chain logistics transportation system based on 5G network and Internet of things system. *Microprocessors and Microsystems*, *80*, 103565.

Li, X., Wang, Z., Gao, S., Hu, R., Zhu, Q., & Wang, L. (2019). An Intelligent Context-Aware Management Framework for Cold Chain Logistics Distribution. *IEEE Transactions on Intelligent Transportation Systems*, *20*(12), 4553–4566. doi:10.1109/TITS.2018.2889069

Li, Y., Lim, M. K., & Tseng, M. L. (2019). A green vehicle routing model based on modified particle swarm optimization for cold chain logistics. *Industrial Management & Data Systems*, *119*(3), 473–494. doi:10.1108/IMDS-07-2018-0314

Liao, Z., Quan, Y., Jian, K., & Guo, Y. 2019, December. Research on the optimization model of cold chain logistics distribution path under the constraint of carbon emission. In Journal of Physics: Conference Series (Vol. 1423, No. 1, p. 012034). IOP Publishing. doi:10.1088/1742-6596/1423/1/012034

Liu, G., Hu, J., Yang, Y., Xia, S., & Lim, M. K. (2020). Vehicle Routing Problem in Cold Chain Logistics: A Joint Distribution Model with Carbon Trading Mechanisms. *Resources, Conservation and Recycling*, *156*, 104715. doi:10.1016/j.resconrec.2020.104715

Peng, B., Wang, Y., Zahid, S., Wei, G., & Elahi, E. (2020). Platform ecological circle for cold chain logistics enterprises: The value co-creation analysis. *Industrial Management & Data Systems*, *120*(4), 675–691. Advance online publication. doi:10.1108/IMDS-10-2019-0531

Poornima, D., 2020. Energy Efficient Precision Agriculture to Conserve Water, Eliminate Pests and Boost Productivity. *A Systematic Literature Survey, 13*(1), pp. 657–672.

Poornima, D. & Arulselvi, G. (2020). Precision agriculture for pest management on enhanced acoustic signal using improved mel-frequency cepstrum coefficient and deep learning. *Journal of Advanced Research in Dynamical and Control Systems, 12*(Sp.3), pp. 50–65..10.5373/JARDCS/V12SP3/20201238

Qi, C., & Hu, L. (2020). Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss. *Physical Communication*, *40*, 101085. doi:10.1016/j.phycom.2020.101085

Qiao, J. 2019, June. Research on optimizing the distribution route of food cold chain logistics based on modern biotechnology. In AIP Conference Proceedings (Vol. 2110, No. 1, p. 020070). AIP Publishing LLC, doi:10.1063/1.5110864

Qin, G., Tao, F., & Li, L. (2019). A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and carbon emissions. *International Journal of Environmental Research and Public Health*, *16*(4), 576. doi:10.3390/ijerph16040576 PMID:30781502

Song, M. X., Li, J. Q., Han, Y. Q., Han, Y. Y., Liu, L. L., & Sun, Q. (2020). Metaheuristics for solving the vehicle routing problem with the time windows and energy consumption in cold chain logistics. *Applied Soft Computing*, *95*, 106561. doi:10.1016/j.asoc.2020.106561

Wang, Z., Leng, L., Wang, S., Li, G., & Zhao, Y. (2020). A hyperheuristic approach for location-routing problem of cold chain logistics considering fuel consumption. *Computational Intelligence and Neuroscience*, *2020*, 1–17. doi:10.1155/2020/8395754 PMID:32405298

Wang, Z., & Wen, P. (2020). Optimization of a low-carbon two-echelon heterogeneous-fleet vehicle routing for cold chain logistics under mixed time window. *Sustainability*, *12*(5), 1967. doi:10.3390/su12051967

Wei, J. 2019, February. Research on the cold chain logistics distribution system of agricultural products. In IOP Conference Series: Earth and Environmental Science (Vol. 237, No. 5, p. 052050). IOP Publishing, doi:10.1088/1755-1315/237/5/052050

Wei, J., & Lv, S. 2019, February. Research on the Distribution System of Agricultural Products Cold Chain Logistics Based on Internet of Things. In IOP Conference Series: Earth and Environmental Science (Vol. 237, No. 5, p. 052036). IOP Publishing. doi:10.1088/1755-1315/237/5/052036

Xiong, H. (2021). Research on Cold Chain Logistics Distribution Route Based on Ant Colony Optimization Algorithm. *Discrete Dynamics in Nature and Society*.

Zhang, L. Y., Tseng, M. L., Wang, C. H., Xiao, C., & Fei, T. (2019). Low-carbon cold chain logistics using ribonucleic acid-ant colony optimization algorithm. *Journal of Cleaner Production*, *233*, 169–180. doi:10.1016/j.jclepro.2019.05.306