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Article

Business process overhaul in dairy supply chains: An integrated approach of advanced forecasting and vehicle routing techniques

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Abstract: The study explores improving opportunities of forecasting accuracy from the traditional method through advanced forecasting techniques. This enables companies to optimize inventory management, production planning, and reducing the travelling time thorough vehicle route optimization. The article introduced a holistic framework by deploying advanced demand forecasting techniques i.e., AutoRegressive Integrated Moving Average (ARIMA) and Recurrent Neural Network-Long Short-Term Memory (RNN-LSTM) models, and the Vehicle Routing Problem with Time Windows (VRPTW) approach. The actual milk demand data came from the company and two forecasting models, ARIMA and RNN-LSTM, have been deployed using Python Jupyter notebook and compared them in terms of various precision measures. VRPTW established not only the optimal routes for a fleet of six vehicles but also tactical scheduling which contributes to a streamlined and agile raw milk collection process, ensuring a harmonious and resource-efficient operation. The proposed approach succeeded on dropping about 16% of total travel time and capable of making predictions with approximately 2% increased accuracy than before.

Keywords: dairy supply chain; demand forecasting; scheduling; supply chain management; vehicle routing

1. Introduction

HAOY The increasing demand for dairy products in developing countries such as Bangladesh, which help people to get proteins particularly, dairy milk and related items—cream cheese, curd, butter and sweets necessitates increased production to improve both economic situation and the country's agriculture as a whole. Moreover, several factors for instance, urbanization, income level and individual preferences etc. are responsible for the significant growth of dairy industry. Due to the demand changes pattern for dairy products and its significance, it has become essential to ascertain uninterrupted supply chain management and business process redesign explicitly. Therefore, with the above in mind this research set goals to improve the overall supply chain of the dairy products by integrating advanced forecasting technique (for example: ARIMA, RNN-LSTM) to predict demand more accurately with optimized vehicle routing logistics (for instance: VRPTW) (Hossain et al., 2022). Several literatures related to this field studied and provided the following summary in order to find the research question. Elufioye et al. (2024) studied the provides comprehensive review and its impact of artificial intelligence (AI) focusing on demand forecasting and optimizing supply in agricultural supply chains. To integrate location, inventory and routing problems arising in designing a resilient sustainable perishable food supply chain network, a bio-objective optimization model is developed Abbasian et al. (2023). In study of the complex data analysis sourced from various stakeholders, such as suppliers and manufacturers and identify risk, CNN-LSTM method with transfer learning reduced business risk and supports the decision making effectively compared to traditional method (Zhang et al., 2023). Pan et al. (2023) presented a three-party evolutionary game model for digital innovation diffusion, involving core manufacturers, affiliated enterprises and the government where manufacturer sets the optimal stability conditions due to cost consideration while government's reward and punishment mechanism promotes technology diffusion in the market. Li and Donta (2023) explored the link between digital transformation and green supply chain management using AI, specially the XGBoost algorithm, to analyse market demand and extract multi-dimensional features. The SNN-Stacking model outperforms traditional models, aiding resource planning, enhancing supply chain transparency and promoting sustainable business development. The dairy industry faces challenges to keep pace with the changing trends of erratic demand in the world due to dismantled supply chain and ineffective logistics etc. To overcome these obstacles and addresses new scope, a comprehensive redesign of organization for smooth operations is needed (Awad et al., 2021; Malik et al., 2021). In the dairy sector, traditional demand prediction and logistical support techniques frequently fail to provide reliable estimates of demand fluctuations and supply chain network optimization (Choi et al., 2021; Malairajan et al., 2013). Due to these discrepancy, some of the outcomes including-excessive transportation costs, overstock or understock inventory and inconsistent service levels were observed. An integration of advanced demand forecasting techniques for instances ARIMA (Kashyap et al., 2023) with optimized vehicle routing algorithms for milk collection is crucial to tackle these challenges (Gheisariha et al., 2023; Rinaldi et al., 2020; Torres Guerra et al., 2013) and comprehensive business overhaul. Business can improve operational efficiency, decrease wastage, improve customer satisfaction and ultimately increase supply chain surplus which aligned with sustainable goals by leveraging advanced forecasting techniques leading to error minimize (Buics and Süle, 2020; Kashyap et al., 2023). Along with this, deploying optimized vehicle routing strategies considering factors including heterogeneous vehicles, time constraints, and blending process can significantly impact profitability and cost-effectiveness in milk collection networks (Adriano et al., 2019; Gyurián and Gyurián, 2022) ultimately offer overall business competitiveness (Kashyap et al., 2023). An optimized distribution network and agri-food supply chain redesign was studied by Boudahri et al. (2022) in Algeria. Study conducted by Ravichandran et al. (2020) focuses on simulation based vehicle routing incorporating economic and environmental factors for business process redesign. Traveling Salesman Problem (TSP) is an effective tool to optimize dairy delivery routes and reducing overall costs (Palhares and Araújo, 2018). Some vehicle routing techniques including genetic algorithm and mixed integer programming with focusing optimized dairy supply chains using milk-run model significantly reduce transportation costs (Kumar et al., 2022). Another study conducted by Rautela et al. (2017) found significant decrease in distribution costs by applying optimized vehicle route for a state-owned Indian cooperative dairy (Huerta-Soto et al., 2023). In order to improve forecasting and routing efficiency in dairy supply chains, the article

(Jachimczyk et al., 2021) suggests an IoT-based Dairy Supply Chain model with an emphasis on openness and interoperability. The study (Scaria and Joseph, 2014) addressed how to decrease money and enhance customer satisfaction by deploying only vehicle routing strategies without incorporating advanced forecasting techniques (Malairajan et al., 2013). The efficiency of the in-plant milk run system in the automobile industry was improved by a CVRP model while advanced forecasting in dairy supply chains is not specifically addressed in the research (Pereira et al., 2021). Bocewicz et al. (2019) presented a declarative model for milk-run vehicle routing in supply chains integrating forecasting and routing methodologies without focusing on minimizing vehicle downtime and Fang and Stone (2021) focused smart contracts, security and transparency without covering advanced forecasting and vehicle routing strategies on block chain-based dairy logistics ecosystem. Using cutting-edge vehicle routing algorithms, (O'Callaghan et al., 2018) provided a novel milk collection route simulation model with the goal of maximizing transportation efficiency in the Irish dairy industry. Supply chain sustainability improvement, wastage reduction, and optimization operations by incorporating advanced forecasting and truck routing strategies in dairy business was studied by Shamsuddoha et al. (2023). In addition to concentration on sophisticated forecasting methods in dairy supply chains, Elgarej et al. (2020) focused on creating a logistics monitoring system for improving milk collecting routes using IoT technology. For the dairy business in India, an integrated production-distribution planning model (Ghosh and Mondal, 2018) uses vehicle routing and forecasting approaches and modernization of dairy sector involving mathematical approaches such as, AI and machine learning approaches improved supply chain efficiency. The study (Shah, 2016) talks on supply chain management in the dairy industry in India, with an emphasis on private and cooperative models. However, it doesn't really cover advanced forecasting or vehicle routing methods.

For the dairy business in India, an integrated production-distribution planning model (Ghosh and Mondal, 2018) uses vehicle routing and forecasting approaches to maximize profit contribution through MILP formulation and sensitivity analysis. To recapitulate from the above literature, it is evident that in some research, authors dealt with either only advanced demand predicting techniques or some addressed MILP formulation and sensitivity analysis. Very few studies addressed both advanced forecasting and optimized vehicle routing techniques in dairy business supply chain management. Therefore, to tackle above discrepancies among the previous research, this study aims to incorporate the advanced demand predicting with optimized vehicle routing techniques which can significantly streamline operations in the dairy supply chain improving the efficiency and sustainability including employment opportunity and business competitiveness enhancement in both domestic and international markets. To reiterate, this research underscores the critical need for modernizing dairy supply chains through advanced approaches, ultimately fostering growth and encourages collaboration among various supply chain stakeholders-farmers, processors and distributors which ultimately can lead to more synchronized operations and stronger supply chain in the dairy industry.

2. Materials and methods

2.1. Solution steps

The study addresses the increasing demand for raw milk delivery, consumed by nearly 6 billion people worldwide. It aims to develop step-by-step methodologies to optimize milk delivery routes. The research methodology includes several crucial steps, starting with a literature review and culminating in result analysis and discussion. review. They must be provided prior to publication. As seen on **Figure 1** the initial step involves a thorough literature review, examining existing research on dairy supply chain optimization, particularly focusing on demand forecasting, and VRPTW. Following this, the study formulates a mathematical model and methodology, defining the problem, specifying variables, constraints, and parameters. Subsequently, data collection is conducted, gathering historical demand data and geographical information necessary for creating distance matrices.

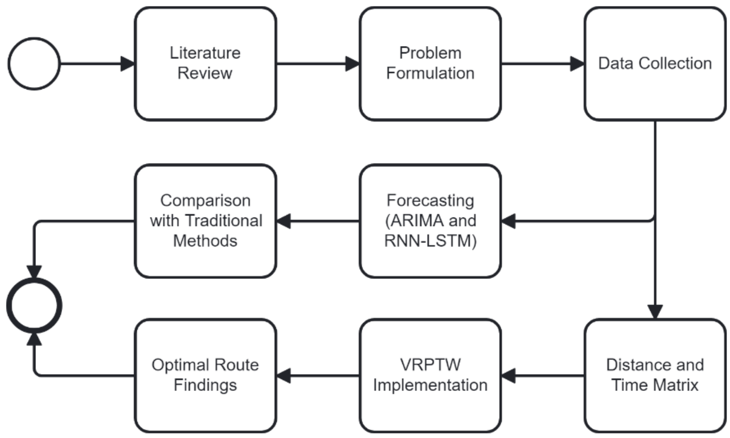


Figure 1. Solution approach.

The study then employs ARIMA and RNN-LSTM models to forecast future raw milk demand, comparing their accuracy to determine the most reliable method. This is followed by creating distance and time matrices using programming tools like Python, which are vital for optimizing vehicle routes. The VRPTW implementation step focuses on finding the most efficient routes for milk collection vehicles by formulating the problem, defining constraints, and optimizing the transportation process to minimize costs and time while adhering to time windows. The study then calculates the optimal number of vehicles needed, along with the total distance and time travelled, ensuring resource allocation and operational efficiency. Finally, the results are presented and discussed, evaluating the effectiveness of the methodologies, comparing outcomes, and providing insights and recommendations for further improvements in dairy supply chain optimization.

2.2. Model formulation

2.2.1. ARIMA model formulation

ARIMA is a time series forecasting model that combines autoregression (AR), differencing (I), and moving averages (MA). The ARIMA (p, d, q) model can be represented as follows (Ariton, 2021):

$$Yt = \mu + \phi 1Yt - 1 + \phi 2Yt - 2 + \ldots + \phi pYt - p + \epsilon t - \theta 1\epsilon t - 1 - \theta 2\epsilon t - 2 - \ldots - \theta q\epsilon t - q$$

where:

Yt is the time series at time *t*.

μ is the constant term.

ϕi are the autoregressive coefficients.

ϵt is the white noise error term at time *t*.

θi are the moving average coefficients.

p is the order of the autoregressive part.

d is the degree of differencing.

q is the order of the moving average part.

2.2.2. RNN-LSTM model formulation

The formulation for a single LSTM unit in a time series forecasting context can be represented as follows (Chauhan, 2020):

$ft = \sigma g(Wf \cdot [ht-1,xt]+bf)$

$it = \sigma g(Wi \cdot [ht-1,xt]+bi)$

$C\sim t = tanh(WC \cdot [ht-1,xt]+bC)$

$Ct = ft \cdot Ct-1+it \cdot C\sim t$

$ot = \sigma g(Wo \cdot [ht-1,xt]+bo)$

$ht = ot \cdot tanh(Ct)$

where:

xt is the input at time t.

ht is the hidden state at time t.

ft, *it*, *C~t*, *Ct*, *ot* are the forget gate, input gate, candidate memory cell, memory cell, and output gate respectively.

Wf, *Wi*, *WC*, *Wo* are weight matrices for different gates.

bf, *bi*, *bC*, *bo* are bias terms.

σg is the sigmoid activation function.

tanh is the hyperbolic tangent activation function.

2.2.3. Mathematical model formulation for VRPTW

VRPTW can be formulated as a mathematical optimization problem. Here is a mathematical model formulation for VRPTW:

Assume,

n = Number of points (0 = Processing Plant, 1…..*n* = Firm Location).

d_{ij} = Distance of transportation from point I to j.

$x_{ij2} = \begin{cases} 1, if\ vehicle\ goes\ from\ firm\ i\ to\ j \\ \quad 0,\ otherwise \end{cases}$

q_j = Capacity of firm *i*.

c = Capacity of vehicle

Objective function,

Minimize

$$\sum_{v=1}^{m} \sum_{i=o}^{n} \sum_{j=o}^{n} d_{ij} x_{ijv}$$

Constraints,

$$\sum_{v=1}^{m} \sum_{i=o}^{n} x_{ijv} = 1$$

$\forall_{ij} € \{1......n\}$ …………………….. (i)

(i) Ensure that every firm is visited once.

$$\sum_{j=1}^{n} x_{ijv} \leq 1$$

$\forall_{ij} € \{1......m\}$ …………………….. (ii)

(ii) Ensure that every vehicle arrives again at the processing plant if it leaves to firm.

$$\sum_{i=0}^{n} x_{ijv} = \sum_{i=o}^{n} x_{ijv}$$

$\forall_{j} € \{0......n\}, \forall € \{1......m\}$ …………………….. (iii)

(iii) Ensure that number of times a vehicle enters a node is equal to the number of time its leave that node.

$$\sum_{i=0}^{n} \sum_{j=1}^{n} \mathrm{q_j}\, x_{ijv} \leq c$$

$\forall_{v} € \{1......m\}$ …………………….. (iv)

(iv) Ensure that the vehicle cannot carry more than its capacity.

$q_1 = q_2 = ... = q_n \quad \forall_j € \{1......n\}$ …………………….. (v)

(v) Means all vehicle has same capability.

$a_i \leq s_i < b_i \quad \forall_i € \{0......n\}$ …………………….. (vi)

(vi) Ensure that a vehicle is started serving a custom in the time window of the customer.

$x_{ij} € \{0, 1\} \quad \forall_{i,j} = (0......n)$ …………………….. (vii)

(vii) Means all variables are integer.

$$\sum_{rv\, €\, ø} \mathrm{a_{jv}} z_v \geq 1$$

$\forall_j € \{1......n\}$ …………………….. (viii)

(viii) Ensure that all firm are visited.

where,

$$a_{jv} = \begin{cases} 1, if\ route\ rv\ is\ visited, \\ 0,\ otherwise \end{cases}$$

$$x_{ij2} = \begin{cases} 1, if\ route\ rv\ is\ selected, \\ 0,\ otherwise \end{cases}$$

$\O$ = Set of feasible vehicle route

This method aims to reduce the overall distance driven by all vehicles while taking into account a number of limitations, such as the capacity of each vehicle, the time windows available to each customer, and the moment at which a vehicle begins its journey. Additional concerns, such reducing the number of cars used or distributing the effort among each vehicle, can be reflected in the objective function and constraints. Generally, to develop workable and nearly ideal solutions for the VRPTW, this optimization problem is solved by applying specialized algorithms, including column generation or metaheuristics. (Kelley, 2022).

3. Results

3.1. Demand forecasting

Akij Dairy's raw milk collection process is supported by a robust network of 25 chilling centers, strategically distributed across two divisions: Rajshahi and Khulna. The Rajshahi Division owns 13 chilling centres having a daily capacity of 40,000 Liters. Whereas the Khulna Division contains 12 similar centres supporting 35,000 litres per day (**Figure 2**).

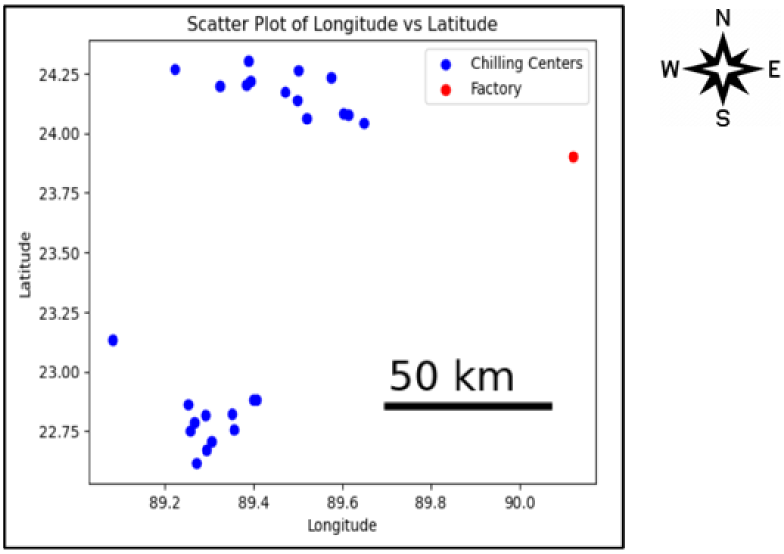


Figure 2. Locations of the factory and chilling centres.

For sustaining the productivity of milk collection and preservation, six dedicated milk trucks, each with a 9600-liter capacity, are deployed. These trucks confirms the milk remains fresh within a temperature range of −2 to 10 degrees Celsius for up to 24 hours post-extraction. The chilling centres which are located in major areas such as Bera, Pabna, and Nakalia, operate in coordination with the factory's schedule to guarantee a harmonized workflow. In the case of demand forecasting, an extensive analysis was conducted using Actual Demand data collected over 46 operating days from Akij Dairy's factory.

This data was utilized to predict the demand for the next 60 days using advanced forecasting techniques like ARIMA and RNN-LSTM. The output of these model have been compared against the traditional methods used by the organization. As seen in **Table 1** key metrics such as MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), and MSE (Mean Squared Error) were used to evaluate the accuracy of these predictions. Using Jupyter notebook, forecasts were generated and carefully judged with actual demand and company forecasts. Similar process has been taken for the RNN-LSTM. This comparative analysis discovered the ARIMA model's superior performance supported by a very lower error percentage of 5.70% as compared to the company's forecast error of 7.97% and the RNN-LSTM model's error of 7.51%, showing the acceptance of the model.

Table 1. Forecasting comparison with existing.

Metrics	Before Implementation	ARIMA	RNN-LSTM
MSE (liters)^2	20,369,600	9,954,490	16,019,600.
MAE (liters)	3784.78	2655.94	3458.99
MAPE	7.97%	5.70%	7.51%

MSE, MAE, MAPE: $p < 0.05$ for ARIMA vs. Before Implementation; $p < 0.05$ for RNN-LSTM vs. Before Implementation.

3.2. Route optimization

This study begins with the optimization process for vehicle routing by creating a VRPTW model with Jupyter Notebook. As can be seen from **Figures 3–5**, the main goal is to determine the best routes for a fleet of six cars to travel in order to reach two different directions of collection places. Time frames are incorporated into this model in recognition of the time limits that must be met in order to service each collection point. This strategic method aims to reduce trip time and resource consumption while optimizing the overall routing process. The ability to negotiate through the complexities of route optimization for many vehicles makes the VRPTW model an invaluable tool for optimizing logistics and attaining a more economical and time-efficient collection process. In order to make mapping on a map easier, the study presents coordinates for each of the cooling spots and the factory. For instance, the factory, AKIJ DAIRY, is located in Dhamrai, Savar, with multiple chilling centers distributed over the Rajshahi and Khulna Divisions. This geographic information is essential for building a distance and time matrix, which forms the basis for figuring out the best routes (**Figure 5**) for the delivery of raw milk. This strategy seeks to optimize the operations of the chilling centres in both divisions by combining spatial and temporal factors to maximize efficiency and reduce transit times. The plant is regarded as the beginning point and the chilling centers as the subsequent destinations in the distance and time matrix (**Figures 3** and **4**). Separate matrices are created for the Rajshahi and Khulna Divisions, considering the 13 chilling centers in Rajshahi and the 12 in Khulna.

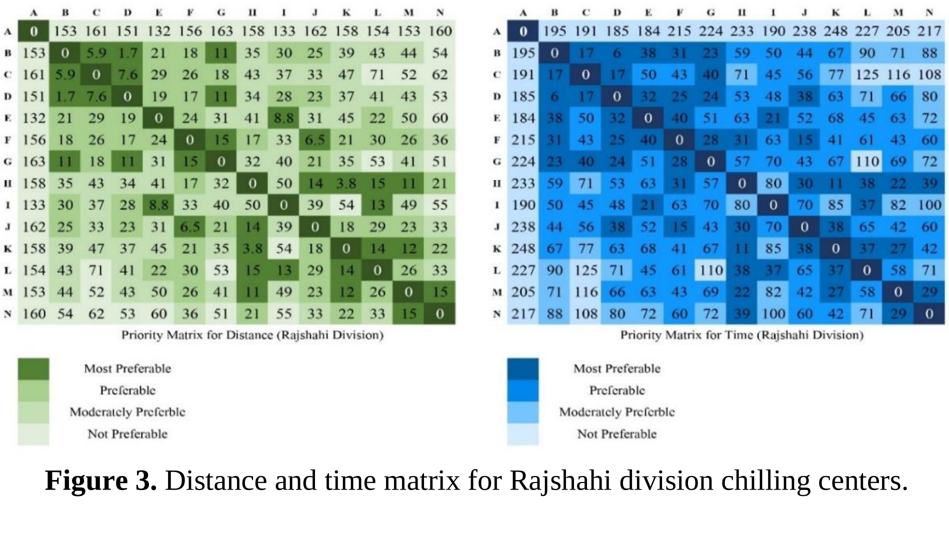


Figure 3. Distance and time matrix for Rajshahi division chilling centers.

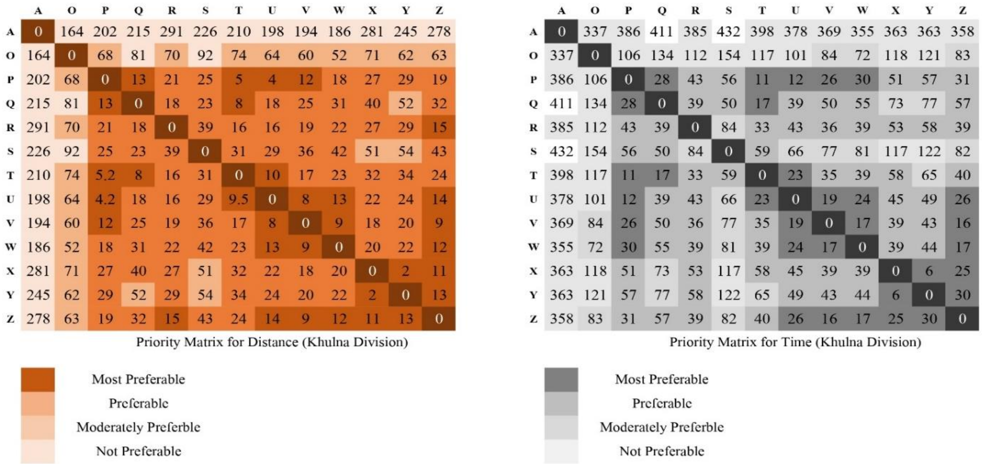


Figure 4. Distance and time matrix for Khulna division chilling centers.

This comprehensive technique offers a thorough understanding of the periods of time and distances required to transfer raw milk from the production to every chilling center (**Figures 3** and **4**). The research considers actual demand, forecasts from ARIMA and RNN-LSTM models, and the capacity of the chilling centers to determine the number of vehicles required each day based on demand.

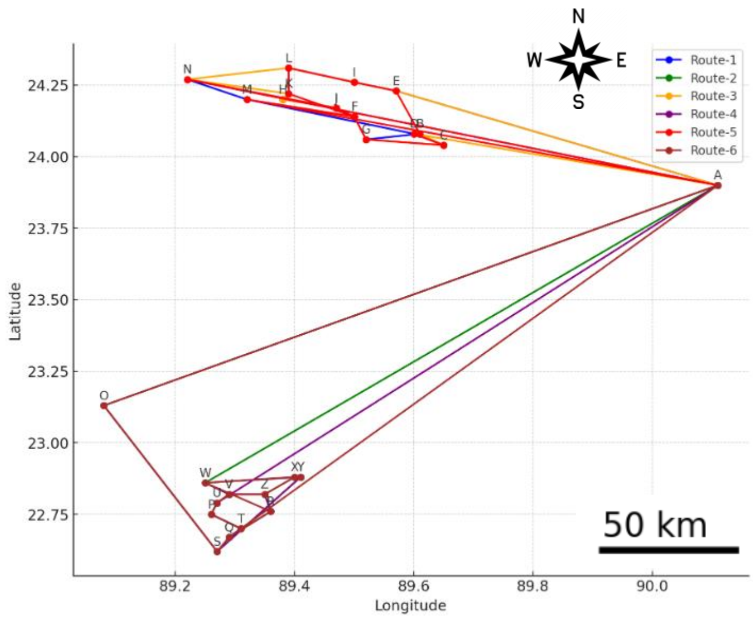


Figure 5. Optimal routes for six different vehicles.

4. Discussion

4.1. Vehicle routing and scheduling

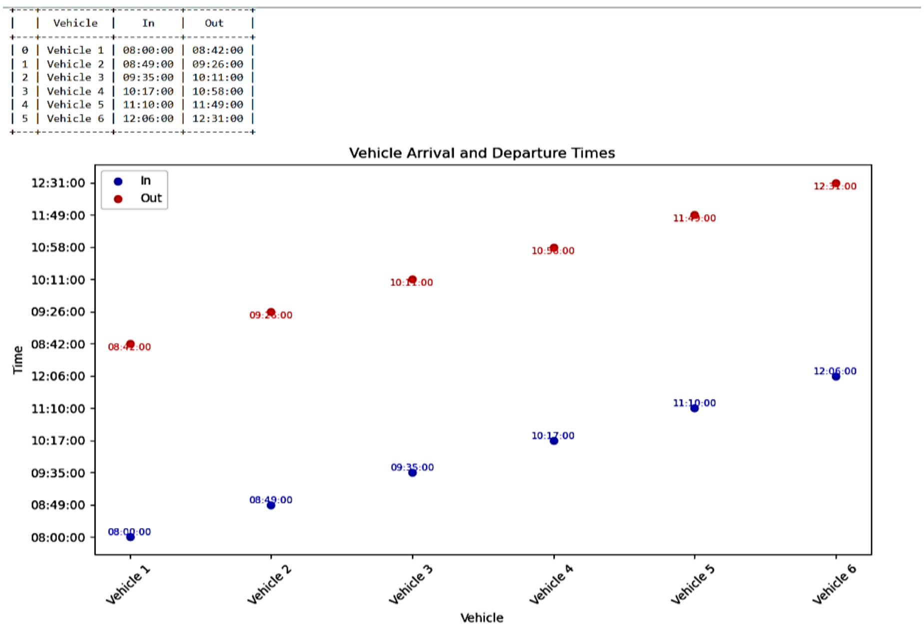
The Rajshahi chilling centres are given precedence due of their close proximity to the facility. As seen in **Table 2** the study takes into account both the actual and anticipated data to determine the number of cars needed to meet demand. For instance, three vehicles from Rajshahi and two from Khulna are required on 1 September 2023, with an actual need of 49,610 litres, making a total of five vehicles for the day. The best routes for the six vehicles are revealed by putting the VRPTW model into practice.

Vehicles go 444 km in 732 min via roads like A → E → I → L → K → H → J → F → G → B → C → D → M → N → A in the Rajshahi Division. The elaboration of all location points are described in Appendix.

Table 2. Optimal vehicle routing.

Vehicle	Route	Total Distance (km)	Total Time (min)
Vehicle-1	A → E → I → L → K → H → J → F → G → B → C → D → M → N → A	444	732
Vehicle-2	A → W → V → U → P → T → Q → R → Z → X → Y → S → O → A	574	1147
Vehicle-3	A → D → B → C → G → F → J → H → K → M → N → L → I → E → A	430	701
Vehicle-4	A → U → P → T → Q → R → Z → V → W → X → Y → S → O → A	598	1147
Vehicle-5	A → M → H → K → L → I → E → B → D → C → G → F → J → N → A	466	754
Vehicle-6	A → T → P → U → V → Z → X → Y → W → R → Q → S → O → A	590	1150

A detailed schedule ensures that vehicles follow planned timetables after the best route has been identified, minimising down on waiting times, making the most use of available resources, and improving operational effectiveness. Each vehicle's arrival and departure times are carefully monitored, as can be seen in the below **Figure 6**. By aligning vehicle availability with demand patterns, this degree of scheduling reduces delays, avoids bottlenecks at loading and unloading locations, and boosts fleet utilisation.



	Vehicle	In	Out
0	Vehicle 1	08:00:00	08:42:00
1	Vehicle 2	08:49:00	09:26:00
2	Vehicle 3	09:35:00	10:11:00
3	Vehicle 4	10:17:00	10:58:00
4	Vehicle 5	11:10:00	11:49:00
5	Vehicle 6	12:06:00	12:31:00

Figure 6. Vehicle scheduling to the factory (in and out), time zone UTC+06:00.

To improve overall efficiency, a specific time slot is allotted to each vehicle in accordance with operating requirements. For instance, vehicle 1 arrives at the factory at 8:00 AM the following day after leaving at 5:00 PM for the chilling centre. This cautious planning reduces bottlenecks and assures a smooth, resource-efficient function for the fleet as a whole.

4.2. Economic implications and environmental impacts

As seen in **Table 3** implementing the VRPTW model resulted in a reduction from six to five vehicles on average, leading to a significant decrease in operational costs. By eliminating one vehicle, the model saves approximately 22,500 Euro on fuel, 36,000 Euro on maintenance, insurances and driver wages. This cost-benefit analysis highlights the model's financial impact, estimating an annual cost reduction of approximately a total of 58,000 Euro if implemented consistently.

Table 3. Comparison of VRPTW performance.

Performance Criteria	Before	After	Percentage Change
Average Vehicle Needed	6	5	−16.67%
Total Distance Travelled	3210	2688	−16.26%
Total Time Taken (Min)	5820	4882	−16.11%

**$p < 0.05$ suggests statistical significance.

Not only this, by minimising the overall distance travelled, the optimised routes promotes sustainability by lowering carbon emissions and fuel usage. These reductions reinforce the significance of effective route planning for long-term ecological impact and are in line with Akij Dairy's commitment to sustainable operations in addition to supporting environmental regulations.

To discuss the seasonal variation impacts on route optimization, the **Table 4** could be proposed to modify schedules and routes in accordance with peak and off-peak seasons, assuring effective resource allocation and lowering transportation expenses.

Table 4. Seasonal demand variation analysis.

Season	Average Demand (Liters)	Optimal Routes Adjustments	Vehicle Allocation
Winter	40,000	Shorter routes, focus on capacity	5 vehicles
Spring	50,000	Standard routes with slight adjustments	6 vehicles
Summer	55,000	Longer routes due to increased demand	6 vehicles
Autumn	45,000	Reduced routes, focus on efficiency	5 vehicles

4.3. Impact on milk quality during transportation

Maintaining appropriate temperatures during transportation is vital for preventing spoilage and preserving the nutritional quality of raw milk. Akij Dairy employs six dedicated milk trucks designed to keep the milk within a temperature range of −2 to 10 degrees Celsius for up to 24 h post-extraction. The optimization of routes, as proposed in the VRPTW model, ensures that transportation times are minimized, thus reducing the risk of temperature fluctuations that could adversely affect milk quality. The strategic scheduling allows for a smooth workflow at the factory and chilling centres, minimizing idle time and ensuring efficient handling. For example, by allotting specific time slots to each vehicle, it can help to mitigate delays that can compromise the quality of milk due to extended exposure to ambient conditions.

4.4. Trade-offs in proposed solution

1) Cost vs. Service Level: Although reducing the number of vehicles from six to five reduces fuel and maintenance expenses, service levels may be impacted if demand spikes without warning. For example, the model's effectiveness may decline during times of high demand, which could cause delays in the delivery and collection of milk. According to the analysis, it is essential to strike a balance between cost containment and service reliability.

2) Flexibility vs. Predictability: Although ARIMA, RNN-LSTM techniques increase predictability, they could make operations more inflexible. The existing routes and schedules might not be flexible enough to handle sudden changes in circumstances when real demand deviates greatly from projections. This emphasises the necessity of an adaptable operational structure that can change in real time to meet changing demand.

3) Resource Allocation vs. Demand variability: Operating expenses are decreased by optimising vehicle usage based on anticipated demand, however there are dangers involved during unanticipated demand spikes. Customer dissatisfaction and missed delivery windows may result from a lack of vehicles. Therefore, when demand exceeds projections, it would be wise to keep a buffer resource or a backup plan that enables the prompt mobilisation of more vehicles.

4) Complexity vs. Usability: Higher initial installation expenses and the need for advanced staff training could result from more complex routing and scheduling algorithms. Some operators may be discouraged from making effective use of the system due to its complexity. Successful adoption requires striking a balance between sophisticated analytical capabilities and intuitive user interfaces and support mechanisms.

5. Conclusion

The investigation carried out aimed at increasing the efficiency of milk collection for Akij Dairy Factory using appropriate data analytic techniques and optimization models. In this case, a geographic criterion was used to sample strategically any 25 points for milk collection and distance to the factory was used. For achieving better demand forecasts, ARIMA and RNN-LSTM techniques were utilized through programming in Python. The findings of the study exhibit the fact that ARIMA and RNN-LSTM models were much better than what the company used to perform the forecasting and also ARIMA produces the best results among them. For instance, notable prominence of ARIMA is seen in improvement of MAE 2656, and MAPE 5.70% over the conventional method employed by the company. In addition, the problem of the Milk collection was also treated as a VRPTW optimization problem. Prior to optimization, the total distance travelled by the trucks was 3210 km and the time spent on the road was 5820 min. After implementing VRPTW model, this was brought down to 2688 km and 4882 min in that order representing 16.23% and 16.09% departure in travel time respectively. The comprehensive approach involved creating detailed schedules for six vehicles, optimizing their routes to minimize travel distances and times and thereby achieving noticeable cost savings and operational efficiencies. The combined approach taken into account the demand forecasting and VRPTW led to a synchronized milk collection process. Accurate demand forecasting assist in Just-In-Time milk collection on the other hand VRPTW optimization makes the best use of trucks needed and minimized travel distances saving valuable times. Predictive analytics and routing optimisation work well together in industries other than dairy that need to handle and transport goods quickly. The requirement to reduce wastage and maintain product freshness is one of the typical logistical issues faced by sectors like fresh produce, pharmaceuticals, and seafood. Demand forecasting can assist more accurately match supply with demand in these situations, preventing stockouts or overstocking. To optimise routes that prioritise shorter delivery times or take into account particular delivery windows requested by clients, the VRPTW model or a comparable route optimisation framework can be modified.

The showcase of implementation of ARIMA and RNN-LSTM models could help many medium-sized and big dairy companies anticipate milk demand more accurately, which would result in more effective collecting procedures. Furthermore, the VRPTW optimisation technique can be modified to fit diverse transportation networks, assisting different dairies in curtailing on trip times and distances. Beyond the dairy industry, these methods are applicable to sectors that deal with perishable items where urgent delivery is essential, such as fresh fruit or pharmaceuticals. For the future scope, it can be integrated with emerging technologies i.e., blockchain and IoT to strengthen the model’s robustness. Further improvements could be testing the model in various geographic and cultural contexts, evaluating seasonal impacts on performance to find potential adjustments required for demand and supply fluctuation. Additionally, analysing the model’s flexibility with regard to different kinds of perishable goods will enhance its applicability across sectors with distinct handling, storage, and transportation requirements. Also, cost-benefit analysis that measures the possible savings from lower mileage, fuel, and vehicle maintenance against the technology investment could help to further substantiate the long term economic benefits of the proposed method. Forecasting accuracy is at risk from demand variations brought on by market conditions (such as seasonal patterns or economic downturns). Demand scenarios ranging from 10% to 30% changes could be taken into account in further analysis.

Author contributions: Conceptualization, GS, MMU, SR and LB; methodology, GS and MMU; software, GS; resources, MMU; writing—original draft preparation, GS and MMU; writing—review and editing, LB and SR; visualization, GS and MMU; supervision, LB and SR; project administration, LB. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest: The authors declare no conflicts of interest.

References

Abbasian, M., Sazvar, Z., & Mohammadisiahroudi, M. (2023). A hybrid optimization method to design a sustainable resilient supply chain in a perishable food industry. Environmental science and pollution research, 30(3), 6080-6103. https://doi.org/10.1007/s11356-022-22115-8

Adriano, D. D., Novaes, A. G., & Wangham, M. S. (2019). Providing a dynamic milk-run vehicle routing using vehicular ad hoc networks. Proceedings of the 9th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications. https://doi.org/10.1145/3345838.335600

Ariton, L. (2021, January 20). A Thorough Introduction To ARIMA Models. Analytics Vidhya. https://medium.com/analytics-vidhya/a-thorough-introduction-to-arima-models-987a24e9ff71

Awad, M., Ndiaye, M., & Osman, A. (2021). Vehicle routing in cold food supply chain logistics: a literature review. The International Journal of Logistics Management, 32(2), 592-617. https://doi.org/10.1108/IJLM-02-2020-0092

Bocewicz, G., Nielsen, P., & Banaszak, Z. (2019). Declarative modeling of a milk-run vehicle routing problem for split and merge supply streams scheduling. Information Systems Architecture and Technology: Proceedings of 39th International Conference on Information Systems Architecture and Technology–ISAT 2018: Part II,

Boudahri, F., Ahmed, A. B., Belkaid, F., & Hacene, R. B. (2022). Modelling and optimization for improving the performance of agri-foods supply chain for milk products. International Journal of Mathematical Models and Methods in Applied Sciences, 16, 83-88. https://doi.org/10.46300/9101.2022.16.15

Buics, L & Süle, E. (2020). Service process excellence in public services. Proceedings of the ENTRENOVA -ENTerprise REsearch InNOVAtion Conference (Online). Vol. 6. No. 1. pp. 173-186.

Chauhan, N. S. (2020, November 29). Introduction to RNN and LSTM. The AI Dream. https://www.theaidream.com/post/introduction-to-rnn-and-lstm

Choi, Y., & Choi, J. W. (2021). A study of job involvement prediction using machine learning technique. International Journal of Organizational Analysis, 29(3), 788-800. https://doi.org/10.1108/IJOA-05-2020-2222

Elgarej, M., Mansouri, K., & Youssfi, M. (2020). Modelling of Logistics Monitoring System for Milk Collection Based on Swarm Intelligence. International Journal of Smart Vehicles and Smart Transportation (IJSVST), 3(2), 59-82. https://doi.org/10.4018/IJSVST.2020070104

Elufioye, O. A., Ike, C. U., Odeyemi, O., Usman, F. O., & Mhlongo, N. Z. (2024). Ai-Driven predictive analytics in agricultural supply chains: a review: assessing the benefits and challenges of ai in forecasting demand and optimizing supply in agriculture. Computer Science & IT Research Journal, 5(2), 473-497.https://doi.org/10.51594/csitrj.v5i2.817

Falatouri, T., Darbanian, F., Brandtner, P., & Udokwu, C. (2022). Predictive analytics for demand forecasting–a comparison of SARIMA and LSTM in retail SCM. Procedia Computer Science, 200, 993-1003. https://doi.org/10.1016/j.procs.2022.01.298

Fang, C., & Stone, W. Z. (2021). An ecosystem for the dairy logistics supply chain with blockchain technology. 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME). https://doi.org/10.1109/ICECCME52200.2021.9591146

Gheisariha, E., Etebari, F., Vahdani, B., & Tavakkoli-Moghaddam, R. (2023). Scheduling and routing of multiple heterogeneous vehicles in a milk collection problem with blending in compartments and time windows. International Journal of Systems Science: Operations & Logistics, 10(1), 2190852. https://doi.org/10.1080/23302674.2023.2190852

Ghosh, D., & Mondal, S. (2018). An integrated production-distribution planning of dairy industry–a case study. International Journal of Logistics Systems and Management, 30(2), 225-245. https://doi.org/10.1504/IJLSM.2018.091963

Gyurián, N. & Gyurián Nagy, N. (2022). The evolution of environmental taxes in Hungary and Slovakia. Acta Oeconomica Universitatis Selye. 11. 10.36007/Acta.2022.11.1.4.

Hossain, S., Jahan, M., & Khatun, F. (2022). Current status of dairy products in Bangladesh: A review on supply and utilization. Int J Bus Manage Soc Res, 11, 609-18. https://doi.org/10.18801/ijbmsr.110222.65

Huerta-Soto, R., Ramirez-Asis, E., Tarazona-Jiménez, J., Nivin-Vargas, L., Norabuena-Figueroa, R., Guzman-Avalos, M., & Reyes-Reyes, C. (2023). Predictable inventory management within dairy supply chain operations. International Journal of Retail & Distribution Management. https://doi.org/10.1108/IJRDM-01-2023-0051

Jachimczyk, B., Tkaczyk, R., Piotrowski, T., Johansson, S., & Kulesza, W. (2021). IoT-based dairy supply chain-an ontological approach. Elektronika ir Elektrotechnika, 27(1), 71-83. https://doi.org/10.5755/j02.eie.27612

Kashyap, A., Shukla, O. J., Jha, B. K., Ramtiyal, B., & Soni, G. (2023). Enhancing sustainable dairy industry growth through cold-supply-chain-integrated production forecasting. Sustainability, 15(22), 16102. https://doi.org/10.3390/su152216102

Kelley, S. (2022, September 7). How to Implement Column Generation for Vehicle Routing. Medium. https://medium.com/@shannon-optimizes/how-to-implement-column-generation-for-vehicle-routing-bdb8027c957f

Kumar, S., Barman, A. G., & Kumar, V. (2022). Study and Analysis of Milk-Run Model for Minimum Cost Under Upstream Supply Chain of a Dairy Plant. Recent Advances in Manufacturing, Automation, Design and Energy Technologies: Proceedings from ICoFT 2020. https://doi.org/10.1007/978-981-16-4222-7_25

Latorre-Biel, J. I., Ferone, D., Juan, A. A., & Faulin, J. (2021). Combining sim heuristics with Petri nets for solving the stochastic vehicle routing problem with correlated demands. Expert Systems with Applications, 168, 114240. https://doi.org/10.1016/j.eswa.2020.114240

Li, T., & Donta, P. K. (2023). Predicting green supply chain impact with snn-stacking model in digital transformation context. Journal of Organizational and End User Computing (JOEUC), 35(1), 1-19.https: doi.org/ 10.4018/JOEUC.334109

Liu, A., Zhu, Q., Xu, L., Lu, Q., & Fan, Y. (2021). Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model. Transportation Research Part E: Logistics and Transportation Review, 150, 102319. https://doi.org/10.1016/j.tre.2021.102319

Malairajan, R., Ganesh, K., Punnniyamoorthy, M., & Anbuudayasankar, S. (2013). Decision support system for real time vehicle routing in indian dairy industry: A case study. International Journal of Information Systems and Supply Chain Management (IJISSCM), 6(4), 77-101. https://doi.org/10.4018/ijisscm.2013100105

Malik, M., Gahlawat, V. K., Mor, R. S., Dahiya, V., & Yadav, M. (2022). Application of Optimization Techniques in the Dairy Supply Chain: A Systematic Review. Logistics, 6(4), Article 4. https://doi.org/10.3390/logistics6040074

O'Callaghan, S., O'Connor, D., & Goulding, D. (2018). Distance optimisation of milk transportation from dairy farms to a processor over a national road network. Journal of International Scientific Publications, 6, 279-296.

Palhares, R. A., & Araújo, M. (2018). Vehicle routing: application of travelling salesman problem in a dairy. 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). https://doi.org/ 10.1109/IEEM.2018.8607472

Pan, W., Miao, L., & Lin, Z. (2023). Analysis of Enterprise Data-Driven Innovation Diffusion Supervision System Based on the Perspective of Green Supply Chain. Journal of Organizational and End User Computing (JOEUC), 35(1), 1-28. https: doi.org/10.4018/JOEUC.333894

Pereira, M. T., Lopes, C., Ferreira, L. P., & Oliveira, S. (2021). A CVRP Model for an In-Plant Milk Run System. Operational Research: IO 2019, Tomar, Portugal, July 22–24, 374, 109. https://doi.org/10.1007/978-3-030-85476-8_9

Rautela, A., Sharma, S., & Bhardwaj, P. (2017). Vehicle routing approach for an efficient distribution: a case of a state-owned Indian cooperative dairy. International Journal of Procurement Management, 10(6), 776-789. https://doi.org/10.1504/IJPM.2017.087319

Ravichandran, M., Naresh, R., & Kandasamy, J. (2020). Supply chain routing in a diary industry using heterogeneous fleet system: simulation-based approach. Journal of The Institution of Engineers (India): Series C, 101(5), 891-911. https://doi.org/10.1007/s40032-020-00588-1

Rinaldi, M., Bottani, E., Solari, F., & Montanari, R. (2020). The milk collection problem with time constraint: An optimization study integrating simulation. Proceedings of the 6th International Food Operations and Processing Simulation Workshop (FoodOPS 2020). https://doi.org/10.46354/i3m.2020.foodops.002

Scaria, C. T., & Joseph, J. (2014). Optimization of transportation route for a milk dairy. International Journal of Engineering Research & Technology, 3(11), 854-859. https://doi.org/IJERTV3IS110577

Shah, D. (2016). Synthesis of Agribusiness Success Models Under Co-Operative and Private Sector in India. Available at SSRN 2885224. http://dx.doi.org/10.2139/ssrn.2885224

Shamout, M. D. (2020). Supply chain data analytics and supply chain agility: a fuzzy sets (fsQCA) approach. International Journal of Organizational Analysis, 28(5), 1055-1067. https://doi.org/10.1108/IJOA-05-2019-1759

Shamsuddoha, M., Nasir, T., & Ibne Hossain, N. U. (2023). Integrating Circular Economy and Reverse Logistics for Achieving Sustainable Dairy Operations. In Data Analytics for Supply Chain Networks (pp. 211-226). Springer. https://doi.org/10.1007/978-3-031-29823-3_8

Torres Guerra, K., Villanueva, C., López Soriano, M., & Moya, E. (2013). Recolección y comercialización de leche en la subcuenca del río Copán, Honduras: La experiencia de los ganaderos en la conformación del Centro de recolección y enfriamiento de leche 'Jorge Bueso. Serie Técnica. Boletín Técnico.

Zhang, Y., & Shankar, A. (2023). Enhancing Supply Chain Transparency and Risk Management Using CNN-LSTM With Transfer Learning. Journal of Organizational and End User Computing (JOEUC), 35(1), 1-22. https: doi.org/10.4018/JOEUC.333472

Appendix

Table A1. Location details of different dairy centres.

Point	Location Address	Latitude	Longitude
A	AKIJ DAIRY, Dhamrai, Savar	23.90	90.11
B	Akij Dairy,Bera,Pabna	24.08	89.61
C	Akij Dairy, Nakalia	24.04	89.65
D	Akij Dairy, Bera	24.08	89.60
E	Akij Dairy, Talgachi	24.23	89.57
F	Demra, Akij Dairy	24.14	89.50
G	Akij Dairy Ltd. Nondonpur	24.06	89.52
H	Akij Dairy, Jogatola	24.20	89.38
I	Akij Dairy, Mohonpur	24.26	89.50
J	Akij Dairy, Sonahara	24.17	89.47
K	Akij Dairy, Bhangura	24.22	89.39
L	Akij Dairy, Satbaria	24.31	89.39
M	Akij Dairy, Mohela	24.20	89.32
N	Akij Dairy, Jonail	24.27	89.22
O	Akij Dairy Shreerampur	23.13	89.08
P	Akij Dairy, Mohonodi	22.75	89.26
Q	Akij Dairy, Mahmudkati	22.67	89.29
R	Akij Dairy, Mothertala	22.76	89.36
S	Akij Dairy, Baka	22.62	89.27
T	Akij Dairy, Kachikata	22.70	89.31
U	Akij Dairy Chandirpur	22.79	89.27
V	Akij Dairy, Maguraghona	22.82	89.29
W	Akij Dairy, Mangolkot	22.86	89.25
X	Akij Dairy, Shapur	22.88	89.40
Y	Akij Dairy, Shapur Fultona Rd	22.88	89.41
Z	Akij Dairy, Dumuria	22.82	89.35