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SEASONAL RECRUITING POLICIES FOR TABLE GRAPE PACKING OPERATIONS: A HYBRID SIMULATION MODELLING STUDY

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ABSTRACT

The packing process is a critical post-harvesting activity in table grape industry. Workers in packing stations are hired under seasonal contracts because of product seasonality and operations labor intensity. Seasonal workers, however, are usually characterized by inconsistent performance, high turnover and experience variation which leads to low productivity and high waste. Few mathematical models were used for evaluating fresh products packing operations, but in a deterministic nature which hinders the complexity and dynamics of the business processes. Hence, a hybrid Discrete Event Simulation (DES) and Agent-Based Modelling (ABM) are employed to evaluate a set of seasonal recruiting policies in a large grape packing station. The paper aims to investigate the impact of workers experience on packing operations efficiency. The model outcomes demonstrate the improvement in operations efficiency and total running cost (about 20% savings) that can be achieved when applying optimal recruiting policies that reduce labors variations.

1 INTRODUCTION

The current growth in the world population and the global economic development have resulted in a high demand on food products. In a competitive food markets, customers' requirements became stringent in terms of food safety, quality, and price. Table grape growers face the same challenges and they need to demonstrate high operational efficiency and effective supply chain cost strategies (Mesabbah et al. 2016). The packing process is a critical activity in the table grape supply chain and often involves series of activities including receiving, sorting, packing and storing grapes received from the vineyards. In order to perform these activities efficiently and in cost-effective way, high skilled workers are required to be recruited at the harvesting season (Blanco et al. 2005, Lambert et al. 2014).

The productivity of packing operations is intertwined with workers' accumulated experience and learned skills (Becker 2009). Although the relationship is intrinsic, little attention was given to the impact of workers experience on packing process performance. This raised many questions including; Does workers experience impact the overall productivity, quality, waste and total operational cost of packing operation? Do hiring policies play a role in improving business performance?

In order to address these questions, analytical models that simulate a grape packing station is developed to help decision-makers to investigate the impact of workers experience and labor hiring policies on the process productivity. However, the applications of these models on table grape supply chain are limited (Bohle, Maturana, and Vera 2010, Mesabbah et al. 2016). This paper therefore, presents a hybrid simulation model that integrates Discrete Event Simulation (DES) and Agent-based Modelling (ABM) to bridge this gap. The DES is used to model system's complexity and dynamics that cannot be modeled by deterministic mathematical models (Mittal and Krejci 2015). ABM on the other hand will explain the impact of the heterogeneous features of the packing process including labor seasonality and human experience (Higgins et al. 2010).

2 LITERATURE REVIEW

Improving packing processes in the fresh produce supply chains received extensive attention between practitioners and researchers alike. This is explained due to their role in protecting food products, extending shelf-life time and promoting attractiveness to customer (Sunk, Kuhlang, and Sihn 2015, Marsh and Bugusu 2007). Many articles discussed solutions to reduce packing cost, improve its performance, facilitate decision making and optimize planning activities (Jiao, 2012, Jiao, 2015). Transportation time from the vineyard to packing stations, resource planning and delivery costs are significant decisions that are evaluated in the literature using mathematical and simulation techniques (Ahumada and Villalobos 2011a). A discrete event simulation, for instance, was used to evaluate initiatives that reduce the waste in labor's working hours in a tomato greenhouse (Bechar et al. (2007). A stochastic and simulation model are combined in another study to optimize the recruiting practices for the seasonal workers in fresh-produce supply chain and measure their impact on productivity and food wastage (Kim et al. 2013). In a similar study, the effect of hiring permanent staff on products packing performance in apple and pears farms has been investigated analytically by Blanco et al. (2005). Storage capacity of fruit palletization in South African has also been optimized using simulation optimization methodologies (Ortmann, Van Vuuren, and Van Dyk 2006).

Similar to the simulation approach, agent-based models are applied in various manufacturing and distribution contexts in order to improve the decision-making process (Nilsson and Darley 2006). However, there is no ABM applications in agri-fresh produce supply chain (AFPSC) have investigated the impact of labors recruitment policies and labor skills and experience on packing stations performance. Ahumada and Villalobos (2009) have also mentioned that using simulation approaches to plan and optimize AFPSC are underutilized comparing to the mathematical models. The activities in table grape industry is characterized by seasonality and encompass heterogeneous features that the mathematical models alone cannot model effectively. Therefore, a hybrid simulation model of DES and ABM can be a suitable methodology to model the heterogeneous characteristics in AFPSC, in particular labor experience and productivity (Mesabbah et al. 2016). The paper adopts a hybrid approach that integrates DES that depicts dynamics and complexities of packing operations and ABM that incorporates the heterogeneous characteristics of the seasonal workers. There is a general growing interest in the application of hybrid simulation approaches due to its capabilities to overcome the limitation of single approach solutions (Martinez-moyano and Macal 2016, Brailsford et al. 2013).

3 TABLE GRAPE PACKING AND SEASONAL PACKERS ISSUE

3.1 Case Study - Ragab Farms

Ragab Farms is a third-generation producer and exporter of premium fresh produce based in the North of Egypt. Stretching over 1700 acres of reclaimed desert land, the company has more than 300 employees and blends local competence with global expertise to export its fresh products to international markets. Ragab Farms manages a sizeable scale of operations which involve the production and management of ten thousand tons of produce. The table grapes division is one of the most important business units within the organization. It operates on 300 acres of land and produces 10 varieties of grapes, the majority of which are exported through the company's export subsidiary from Mid-May until the end of August.

The grapes packing process sits at the core of the export operation and determines, to a great extent, the efficiency of the supply chain and the quality of the final product. Once picked in the field, grapes are loaded in plastic crates and transported by truck to the packing station. The fruit is offloaded in an air-conditioned receiving area, then is carried by conveyors along packing lanes to be packed by labor into 500 gram punnets which would be ultimately sold to retail consumers. Packing process relies entirely on the manual skill of the packing labor who work in groups of two to three on packing tables. In addition to packing the fruit into the punnets, their other tasks include: 1) Visually inspecting the fruits, 2) Removing any defective berries, 3) Adjusting the weight of each punnet using a digital scale, and 4) Stacking each ten punnets into one 5 kg box. Accordingly, their role has a major impact on a number of performance indicators including productivity, fruit wastes, and quality of the final product.

The hybrid model developed represents the packing operations for received quantities from the vineyards over five weeks (from 12th May to 18th June). Packing station under study comprises four packing lines, each line has a set of packing tables where packers are assigned to perform packing activities. The maximum number of tables in the station that can operate simultaneously is 95. Each packing table can operate with two or three packers according to the work volumes. Daily received quantities (in tons) can vary according to harvesting conditions (Figure 1).

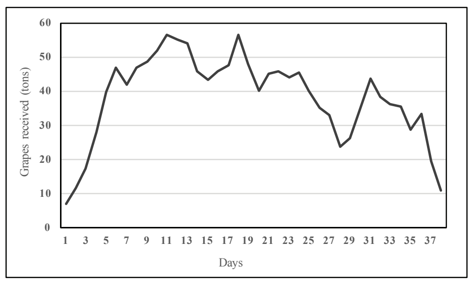


Figure 1. Daily Received Quantity from the vineyards 2016.

3.2 Problem Definition

The biological deterioration of table grapes starts directly after harvesting (Nagasawa, Kotani, and Morizawa 2009). The packing quality plays instrumental role in preserving grape quality and freshness during distribution activities (Blanco et al. 2005). In Ragab Farms, grapes are transported from the vineyards to the packing station in a daily basis. Packing stations managers provide extra attention to two main issues during operations; first, the packing process must start directly, with no delay, after receiving grape from the vineyard. Reducing the waiting time of the grape in the receiving area helps to preserve products quality and shelf-life time. Second, it is important to maintain grape waste in its minimum level by developing packers skills and maintain the most experienced one. Employing efficient recruitment plans and optimizing labors capacity play key roles in achieving both objectives.

During 2016, the packing station at Ragab farm received around 1500 tons of grapes. Only 1250 tons were packed as final products and 250 tons (17%) were considered waste. In addition, the average waiting time of the grape in the receiving area, during the season peak, estimated by 24 hours in average. It is believed that improving packers skills and preserving their experience is important to improve farm's performance and productivity.

During the harvesting seasons, packers are recruited on a daily basis based on managers' demand. The recruiting process is basically relying on the seasonal workers from nearby rural areas. However, the fierce competition between growers to recruit skillful workers affects the consistency of workers supply. In addition, recruiting agencies cannot guarantee to supply the same group of labors every day because of the seasonality nature of the process. However, hiring the same packers reduce training efforts and reflect positively on farm's productivity and product quality.

4 HYBRID MODEL DEVELOPMENT

The developed hybrid model allows managers to evaluate different hiring policies for the seasonal packers in Ragab Farm's. It helps farm's managers to select the best hiring policy that can retain experienced packers over the harvesting season and investigate how this impacts labor productivity, hiring costs, losses costs, and operational efficiency. The model consists of five building blocks as shown in Figure 2.

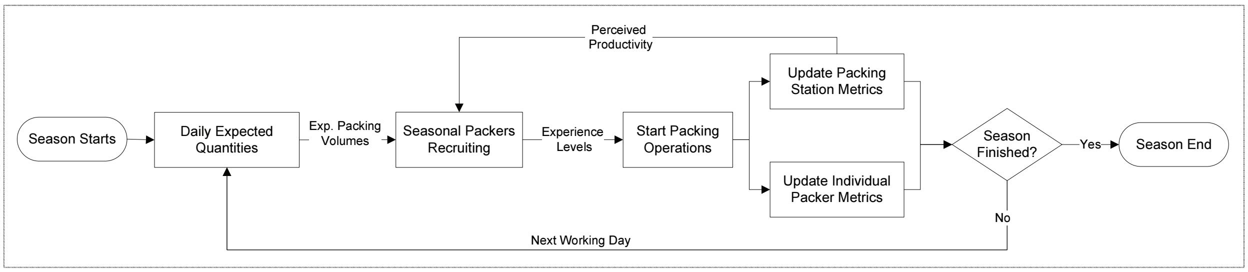


Figure 2. Model Building Blocks.

At the start of harvesting season, manager of packing station receives rough estimates of the expected harvest quantities that can be received at the station. ***"Daily Expected Quantities"*** block is responsible of predicting harvest quantities based on the historical data of the previous seasons (Figure 1). The number of required packers is then estimated based on packers' productivity rate and the expected quantities of harvested grapes. The ***"Seasonal Packers Recruiting"*** block simulates the hiring process of the seasonal packers. The packing processes are then modeled in the ***"Start Packing Operations"*** block and contains the planning of resources capacity, processes structure, and the relationships between system's parameters. The discrete event simulation is used to model the business processes and their dynamics, while the human and equipment in the station are modeled as agents – highlighted in yellow in Figure 3. At the end of every working day, the performance metrics of packing station are updated – ***"Update Packing Station Metrics"*** block – as well as each packer agent metrics – ***"Update Individual Packer Metrics"***.

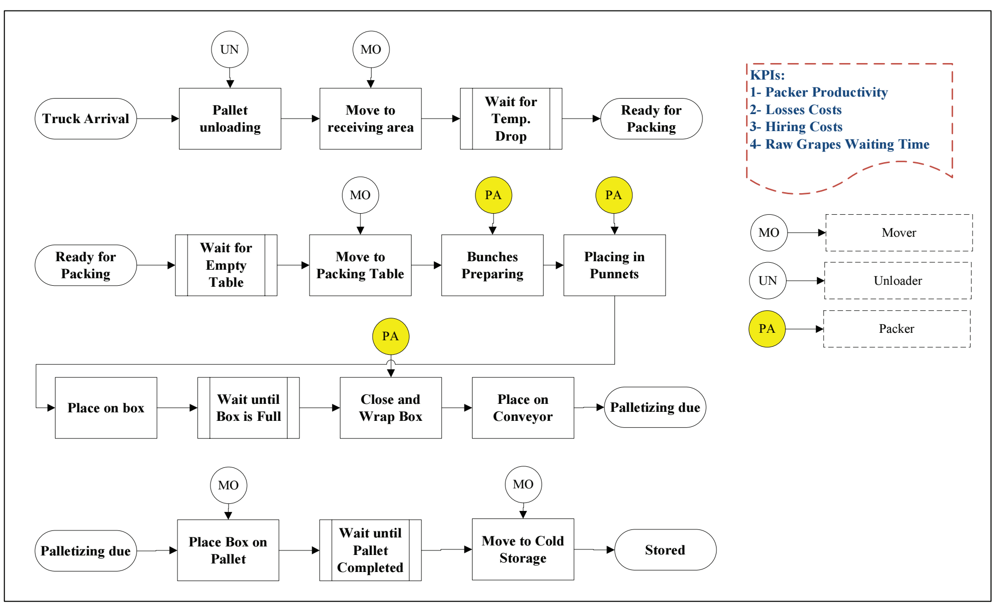


Figure 3. Conceptual Model for Packing Station Operations.

4.1 Mathematical Formulation

Block 1: Daily Expected Quantities to arrive at the packing station $(\widehat{\boldsymbol{Q}})$ are the main factors that controls the number of packers to be recruited at any particular day. This quantity is calculated based on historical figure for the daily received quantities using the following equation:

$$\hat{Q}(t) = \tilde{Q}(t) \cdot (1 + w) \quad (1)$$

Where, $\boldsymbol{t}$ is simulation time (days), $\tilde{Q}$ is historical quantity received at the corresponding simulation day and w is simple random noise between -0.15 and 0.15, to reflect the reality when estimated quantity is deviated from actual one.

Block 2: Seasonal Packers Recruiting The number of packers $(\boldsymbol{N_P})$ required to pack this quantity is calculated using the following equation:

$$\boldsymbol{N_P}(t) = \frac{\hat{Q}(t)+Q_u(t\text{-}1)}{P(t)} \quad (2)$$

Where, $\boldsymbol{Q_u}$ is the unpacked raw grapes from the previous day (if any) , and $\boldsymbol{P}$ is the perceived packer productivity at day $\boldsymbol{t}$. Packers' productivity is a updated in ***"Update Packing Station Metrics"*** block.

Block 3: Start Packing Operations is triggered by the arrival of harvested grape in the receiving area. Grape pallets are unloaded and placed in the receiving area for a while to allow the cooling down of product temperature before the start of packing operations. Afterwards, grapes pallets are moved to the packing area, then the crates are distributed over the packing tables according to their availability. Once a crate is placed on a packing table, the packers pick the grape bunches and perform three main processes as illustrated in agents' state chart in Figure 4: 1) ***Preparing_Bunch*** to remove any damaged and/or inconsistent berries; 2) ***Packing_Punnet*** where bunches are cut and placed in 0.5 kg weighted plastic punnet, then it is placed in a packing box; once the box becomes full (it takes 10 punnets); 3) ***Wrapping_Box*** process take place. Any packer ***At_Packing_Table*** can do any of these processes.

The times for these processes along with the quantities of products waste vary from packer to another according to the experience level. This experience represents the skills that a packer gains either over the current season or previously if she was recruited before. Packers' experience level along with packing cycle times and grapes waste fractions – which both are functions of packer experience – are updated in ***Update Individual Packer Metrics"*** block. Once the work is finished, the performance metrics of packing station and packers are updated.

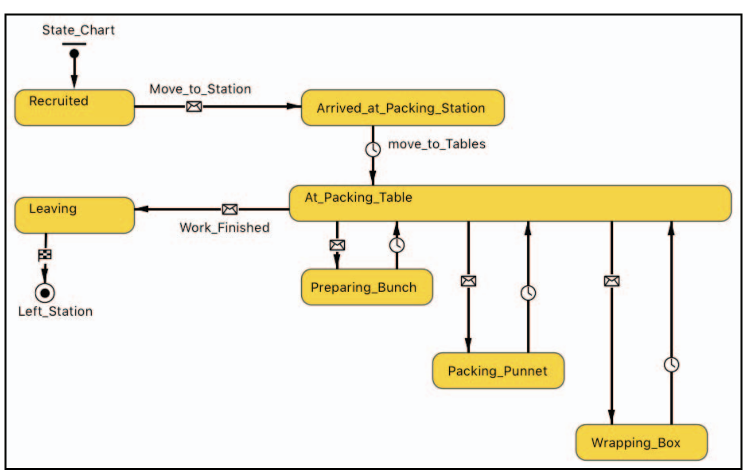


Figure 4. Seasonal Packer State Chart

Block 4: Update Packing Station Metrics block focuses on a set of operational metrics that include: 1) daily packed quantity ($\boldsymbol{Q_p}$); 2) grapes loss quantity ($\boldsymbol{Q_l}$); 3) unpacked quantity ($\boldsymbol{Q_u}$); 4) Average waiting time for packing ($\boldsymbol{AWT}$); 5) grapes loss cost ($\boldsymbol{C_L}$), 6) packers hiring cost ($\boldsymbol{C_P}$), 7) perceived worker productivity ($\boldsymbol{P}$). These metrics are updated according to the following set of equations:

$$Q_p(t) = Q_b(t) \cdot b_w \tag{3}$$

Where $\boldsymbol{Q_b}$ is number of packed boxes and $\boldsymbol{b_w}$ is packed box weight (which is 5 kg).

$$Q_l(t) = \quad Q_h(t) - Q_p(t) \tag{4}$$

$$Q_u(t) = Q_r(t) - Q_h(t) \tag{5}$$

Where $\boldsymbol{Q_h}$ is the handled quantity, which actually moved from receiving area to packing area and $\boldsymbol{Q_r}$ is the received quantity from the vineyards at that day.

$$C_L(t) = l_c \cdot Q_l(t) \tag{6}$$

$$C_P(t) = p_c \cdot N_P(t) \tag{7}$$

Where $\boldsymbol{l_c}$ is grapes loss cost per ton and $\boldsymbol{p_c}$ is hiring cost per packer per day.

$$P(t) = Delay_1\ (P(0), \bar{P}(t), a) \tag{8}$$

Where ($\boldsymbol{Delay_1}$) is first order delay function introduced by Sterman (2000), $\boldsymbol{P(0)}$ is the initial value for the perceived packer productivity and $\boldsymbol{a}$ is time to adjust perceived productivity and $\boldsymbol{\bar{P}}$ is average packer productivity that can be calculated as following:

$$\bar{P}(t) = \frac{Q_h(t)}{N_P(t)} \tag{9}$$

Average waiting time for packing ($\boldsymbol{AWT}$) is tracked based on the difference between the time that a raw pallet becomes ready for packing ($\boldsymbol{Tp_r}$) and the time it is moved to packing area ($\boldsymbol{Tp_m}$). This time difference is accumulated for all the pallets received and divided by total number of raw pallets handled to the current day ($\boldsymbol{t}$). Therefore $\boldsymbol{AWT}$ can be formulated as following:

$$AWT(t) = \frac{\sum_{i=0}^{total\ pallet\ handled} (Tp_{m_i} - Tp_{r_i})}{total\ pallet\ handled} \tag{10}$$

Block 5: Update Individual Packer Metrics block updates metrics for each **recruited** packer. The model assumes a pool of seasonal packer available for recruiting with size notated as ($\mathbf{N_S}$). There are mainly two metrics to be updated in this block: 1) number of working days ($\boldsymbol{D}$) and 2) experience level ($\boldsymbol{E}$). The number of working days for each packer is updated as following:

$$D_i(t) = \begin{cases} D_i(t\text{-}1) + 1, & if\ packer\ i\ is\ recruited\ at\ day\ t \\ D_i(t\text{-}1), & Otherwise \end{cases} \qquad \forall\ i = 1,2,..,\mathrm{N_S} \tag{11}$$

The concept of continuous improvement and learning curves introduced by Zangwill and Kantor (1998) is used to model updating packer's experience level using the following equation:

$$E_i(t) = \min\ (E^m,\ E_i(0) \cdot e^{r \cdot D_i(t)}) \qquad \forall\ i = 1,2,..,\mathrm{N_S} \tag{12}$$

Where $\boldsymbol{r}$ is a learning curve parameter, $\boldsymbol{E(0)}$ is the initial experience level and $\boldsymbol{E^m}$ is the maximum experience level. Next section discusses data collected for this model as well as the developed statistical distributions of loss fractions and times of the main packing processes for each packer.

4.2 Data Collection

The primary data in this research are collected based on: 1) historical data based on season 2016; 2) series of interviews with the packers along with the station managers; and 3) On-site observations for packing and handling processes. Table 1 illustrates model parameters and their description, sources of data and their equations.

Table 1: Model Parameters

PARAMETER	Description	Eq. #	Source
$\boldsymbol{N_U}$	Number of unloaders at the station		Site observations
$\boldsymbol{N_M}$	Number of movers at the station		Site observations
$\boldsymbol{N_T}$	Number of packing tables at the station		Site observations
$\boldsymbol{b_w}$	Packed box weight	3	Internal records
$\boldsymbol{l_c}$	Cost for grape losses per ton	6	Internal records
$\boldsymbol{p_c}$	Hiring cost per packer per day	7	Internal records
$\mathbf{N_S}$	Number of seasonal packers in nearby rural areas	11,12	Manager Judgments
$\boldsymbol{P(0)}$	Initial perceived worker's productivity	8	Manager Judgments
$\boldsymbol{a}$	Time to adjust worker's productivity	8	Manager Judgments
$\boldsymbol{m_{pr_{max}}}, \boldsymbol{m_{pr_{min}}}$	Mean time to **preparing bunch** for least and most experienced packers respectively		Site observations
$\boldsymbol{m_{pp_{max}}}, \boldsymbol{m_{pp_{min}}}$	Mean time to **packing punnet** for least and most experienced packers respectively		Site observations
$\boldsymbol{m_{w_{max}}}, \boldsymbol{m_{w_{min}}}$	Mean time to **wrapping box** for least and most experienced packers respectively		Site observations
$\boldsymbol{l_{max}}, \boldsymbol{l_{min}}$	Mean **loss fraction** resulted by least and most experienced packers respectively		Site observations
$\boldsymbol{r}$	learning curve parameter	12	Assumption
$\boldsymbol{E^m}$	The maximum experience level for seasonal worker	12	Assumption
OTHER	Mean time for the other processes (e.g., pallets unloading) in Figure 3		Site observations

To reflect the variations in packers' experience, the model initializes each packer with random experience level $(\boldsymbol{E(0)})$ between **1** and **5** at the start of the season (where 5 means the highest experience level). The statistical analysis of the processing time data of the three packing processes indicates that ***Preparing_Bunch, Packing_Punnet and Wrapping_Box*** processing time are distributed as **Lognormal** distribution with standard deviation equals to 0.5, 0.5 and 0.25 respectively. The mean processing time of the three processes vary from packer to another based on the experience level. They are estimated by comparing the performance of the lowest experienced packers at the beginning of the season against their performance at the end of season, the results are presented in Table 2.
A similar analysis was conducted to drive the statistical distribution of ***Loss_Fraction*** parameter for the least and the most experienced packer. It was found that the ***Loss_Fraction*** of any packer follows **Normal** distribution with a standard deviation 0.02 and mean value varies according to packers' experience level (Table 2). Finally, the model assumes linear relationship between packer's experience level and means of the statistical distributions as illustrated in Figure 5.

Table 2: Mean Values for the Statistical Distributions for Least and Most Experienced Packers

	Least Experienced	Most Experienced
PREPARING_BUNCH	$\boldsymbol{m_{pr_{max}}} = 3.40$	$\boldsymbol{m_{pr_{min}}} = 2.30$
PACKING_PUNNET	$\boldsymbol{m_{pp_{max}}} = 3.1$	$\boldsymbol{m_{pp_{min}}} = 2.07$
WRAPPING_BOX	$\boldsymbol{m_{w_{max}}} = 3.52$	$\boldsymbol{m_{w_{min}}} = 2.99$
LOSSES_FRACTION	$\boldsymbol{l_{max}} = 0.2$	$\boldsymbol{l_{min}} = 0.05$

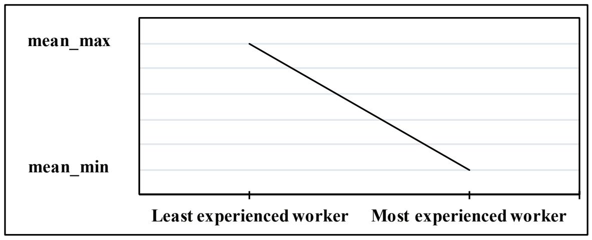


Figure 5. Worker's experience Relationship with distributions means

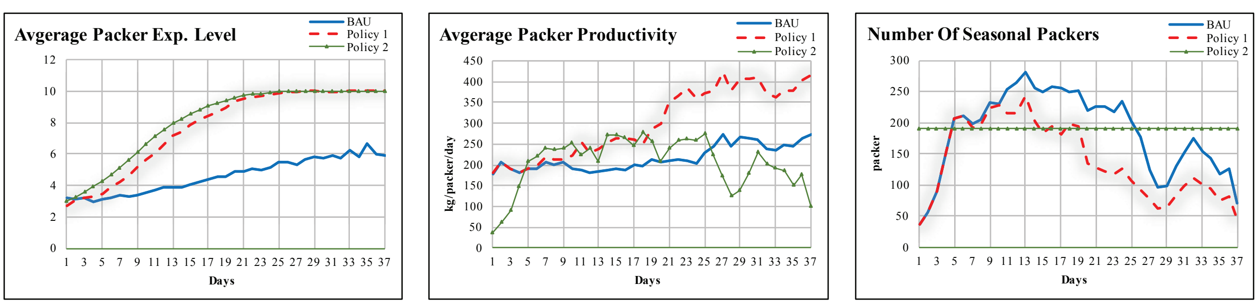
5 OPERATIONAL IMPLICATIONS

The main objective of the model is to investigate different recruiting policies for the seasonal grape packers and try to understand how these policies impact packing station performance. To achieve this objective three different scenarios are evaluated using the hybrid simulation model.

Under business as usual policy (***BAU)*** the unit manager decides how many packers **(N_P)** to recruit at any particular day based on the expected quantity of harvested grapes in the receiving area. Workers agencies secure the required number of packers, but that does not imply calling for the trained packers again to the station. They claim that the variability in the required number of packers and market demands can influence their ability to supply same packers every day.

The First proposed policy ***(P1)*** tries to resolve this issue by offering **extra hiring cost (25%)** per packer (p_c) under a condition that worker agency secure the required number of packers where the priority is given to the packers who worked previously in the station. On the other hand, the managers under the second policy ***(P2)*** will recruit a **fixed number of packers** over the season (i.e., N_P will be constant). In this scenario the recruiter will be incentivized to bring the same people every day.

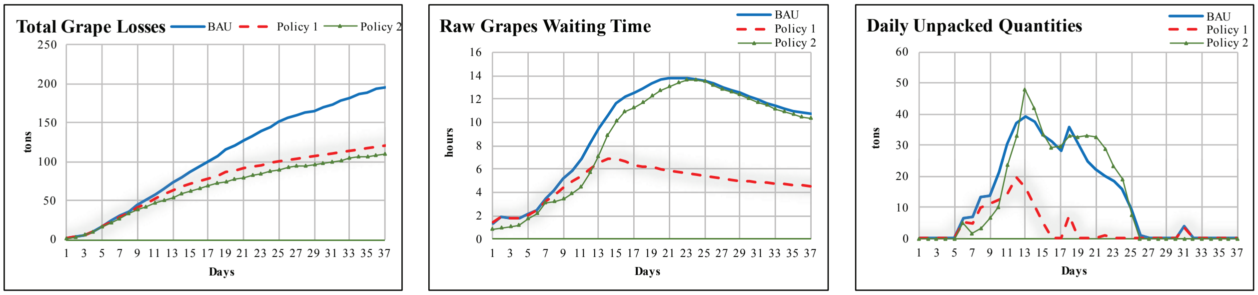
It is noted that the impact of reducing recruitment variations of packers reflects the development of packer's experience level significantly under the three policies (Figure 6.a). Hiring same packers (under ***P2***) or the most recruited ones (under ***P1***) at the station allows rapid development of the packers experience level on both individual and collective levels, which reduce the packing processing times. As a result this positively impacts packers' productivity and, hence, number of packers needed, this is the case in ***P1*** compared to ***BAU*** (Figures 6.b and 6.c). However, in ***P2*** the productivity collapses after nearly two weeks. This can be justified in light of equation (9) where number of packers (N_P), the denominator, is fixed at the same time that daily receiving quantity is decreasing (and consequently the handled quantity (Q_h), the numerator) as presented in Figure 1.



(a) (b) (c)

Figure 6. Average Packer Experience level and Productivity and Number of Packers recruited under the three scenarios

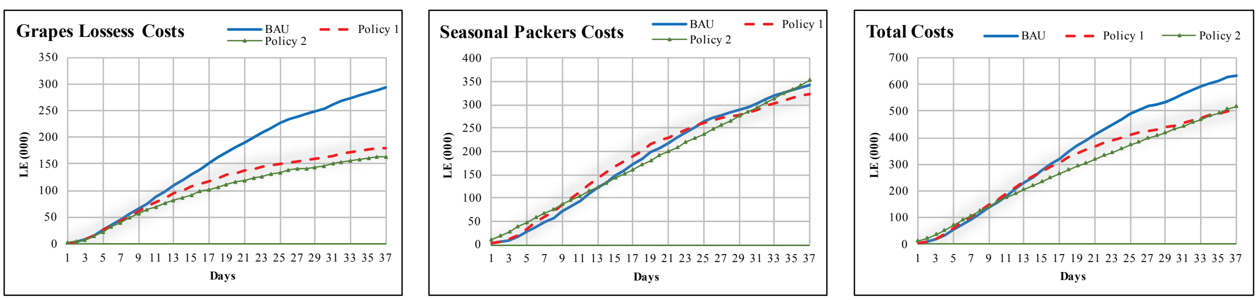
More positive implications of the proposed policies can be observed when considering their impact on grape waste during packing (Figure 7.a). Although it is not a significant difference, but Figure 7.a suggests that ***P2*** is performing better than ***P1*** on saving grape waste. This can be justified in the light of Figure 6.a, where rate of experience improving is slightly higher under ***P2*** compared to ***P1*** because all packers are hired consistently every working day over season. On the other hand, ***P1*** shows improvement in reducing grapes waiting time compared to ***P2*** which is not better than ***BAU*** in this regard (Figure 7.b). The flexibility in the number of recruited packers in ***P1*** concurrently with their improved experience helped in quicker reduction for accumulated unpacked grapes during season peak (Figure 1).



(a) (b) (c)

Figure 7. Total Grapes Losses, Raw Grapes Waiting time and Daily Unpacked Quantities under the three scenarios

from the financial perspective, the proposed policies can show significant improvement in the total operation costs compared to ***BAU*** policy (Figure 8.c). However, the results indicate that none of the two policies outperforms the other based on the total operational costs. The reason is that because each policy outperforms the other in cost saving over one of the two cost elements (losses costs and hiring costs) and the magnitude of these savings are almost the same (Figure 8.a and 8.b).



(a) (b) (c)

Figure 8. Total Grapes Losses, Total Costs and Seasonal Packers Costs under the three scenarios

6 CONCLUSIONS

The hybrid model suggests that if significant and sustainable improvement is to be achieved in the packing processes of table grape, it has to be in recruiting policies. Primarily to retain experienced workers while considering the impact of this decision on the financial performance. While analytical approaches such as mathematical, simulation and optimization models can support decisions, using an integration solution seem to offer more agile model that is capable to simulating complexity of dynamic relationship in table grape applications. Hybridization of ABM and DES has proven effective in gaining insights of grape packing station through simulating the process activities before evaluating operational strategies and related decisions.

Results have showed that the applied recruiting policy ***(BAU)*** in Ragab Farms is less efficient comparing to the two new policies (i.e. ***P1*** and ***P2***). ***P1*** demands offering experienced workers higher wages because the model outcomes have justified the financial obligations for the return on labor productivity and cycle time reduction. While, ***P2*** calls for a constant number of packers to be hired every day during the whole season. This policy has a significant improvement in reducing wastes of grapes as a result of the build-up experience and training from first day on site.

The model results are well-received by the packing station management team. They appreciate the managerial insights gained and applicability of the model to examine different operational strategies and improvement initiatives. Decision to retain experienced workers is what management sought to implement.

Potential future work may include integrating system dynamics approach to the hybrid model in order to support strategic decisions in grape industry (e.g. capital investments, marketing policies and global distribution). There is also an opportunity to extend the model and consider other post-harvesting functions such as receiving and storing operations.

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