



Improving Hot Mix Asphalt Production Using Computer Simulation and Real Time Optimization

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Abstract: The quality of hot mix asphalt is affected by the quality and consistency of input aggregates and the control of the production process. To improve the quality of hot mix asphalt, both the aggregates gradation and the process variables must be considered. Current practice involves taking samples from actual production and analyzing them in the lab. The entire process can take two hours, which, along with being expensive, is not amenable to real time online process control or even in knowing how much product is actually out of specification. In this paper, an online control system is proposed that can be used to significantly decrease the analysis time and adjust production by using discrete time stochastic simulation combined with algorithmic optimization. Additionally, the system can readily show when a mix is out of specification without lag time or physical experimentation. Results show that this approach can effectively control the production process resulting in improved quality. This is the first known such application in hot mix asphalt online process control. DOI: [10.1061/\(ASCE\)CP.1943-5487.0000302](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000302). © 2014 American Society of Civil Engineers.

Author keywords: Hot mix asphalt; Quality control; Simulation; Real time optimization; Aggregate gradation.

Introduction

Hot mix asphalt (HMA) has a very important part in highway construction and its quality is key to longevity and durability of pavement. Over the past two decades, attention has been given to improving the laboratory tests used for quality control of HMA by making them faster and less variable. Although this has been beneficial, testing is still quite time-consuming and expensive. Online real time control of the HMA process is a goal that has not yet been realized fully (West 2005).

The quality of HMA is affected by the quality of the input aggregate and the production process, and the control of the HMA production process is of fundamental importance in assuring aggregate compliance. However, previous studies (Hall and Williams 2002; Turochy et al. 2006; Turochy and Parker 2007) reported that state agencies' verification testing and the contractor quality control testing can show significant variation with respect to the material analysis. A study developed by the California Department of Transportation (Douglas et al. 1999) analyzed the case when material from more than one plant was delivered to the same jobsite. They recommended some special procedures be implemented when this occurs such as not intermingling different plant material at delivery, making sure sampling is not done with comingled material, and making separate control charts for each plant.

However, in practice, ensuring uniformity of raw material is problematic, at best. The goal of production process control is to improve the ability of the hot mix plant to produce material that is consistent and near target. This goal goes well beyond simply

staying within specification compliance. Because of the time required for current sampling and testing methods (for example, currently four 50 pound samples represent 1,000–3,000 tons of production per day), it is difficult, at best, to speculate on the actual amount of production variation. Each quality control sample typically only represents 0.005% of the production or stated another way, each sample represents 20,000 units of production.

Because of these widespread quality issues, researchers have proposed methods to implement quality control for HMA. Guo uses an uncertainty analytic hierarchy process method to improve the quality of HMA (Guo et al. 2009); it is based on a large amount of data collected from actual asphalt production and laboratory testing results. Tsai and Monismith (2009) describe a methodology to determine a sampling scheme and selection of sample size for quality control of HMA. Gopalakrishnan et al. (2008) uses computer simulations to study the compaction process in HMA. White et al. (2002) establish an online database to monitor hot mix asphalt projects throughout their life cycles and bring computing technology and HMA construction together to create real time construction tools. Kabadurmus et al. (2010) presents a basic simulation methodology to establish an online process control of HMA. Kabadurmus's effort provided the earlier version of the optimization algorithm used within this paper. Other than this last paper, the quality control efforts cited above did not approach an online (real time) system addressing production quality. Instead they are offline methods based on data repositories. This still leaves the considerable problems of both time lag in detecting out-of-specification mix and expensive and intermittent physical testing of mix.

The purpose of this paper is to develop a more robust online control model that can be used for aggregate gradation control to improve the quality of the HMA production process and represents the first known such effort. This paper considers varying influence elements, including gradation variation in the cold-feed bins, the job mix formula (JMF) tolerance set by the customer, and several control policies. The HMA online control system adjusts the proportion from each bin of aggregate to optimize quality once it detects that the process is departing from a controlled state. The hardware and data-processing software to obtain real time (that is, continuous) measurements is a major component for a complete

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Note. This manuscript was submitted on July 24, 2012; approved on March 5, 2013; published online on March 7, 2013. Discussion period open until July 24, 2014; separate discussions must be submitted for individual papers. This paper is part of the *Journal of Computing in Civil Engineering*, © ASCE, ISSN 0887-3801/04014011(8)/\$25.00.

process control system. Two technologies have potential to accomplish the physical measurement of aggregate gradation in real time in a production setting. They are optical pattern recognition and line-laser imaging. These technologies are currently rapidly improving and may be the enabler to progress asphalt plant production process control.

Background of HMA Production and Quality Assurance

The typical HMA plant is a drum plant (see Brown et al. 2009 for a good overview). First, aggregates are fed into the cold-feed bins (to be used in the production) and are continuously released onto the main conveyor in specific amounts as required by the JMF. Usually the JMF is dictated by state transportation agencies based on the type of project. The aggregate blend is then conveyed to the drum where the aggregate is heated and asphalt and the other required components are added. Finally, the finished hot mix asphalt is stored in silos before it is transferred to a paving site (Brown et al. 2009). The two main factors in assuring good quality HMA product are the amount of asphalt and the blended aggregate gradation. Aggregate gradation is calculated by the percentage aggregate passing each sieve, and normally eight different sieve sizes are used to define the requirement of a JMF.

The aggregates consist of crush particles, natural sand, friction aggregate, and other elements. Due to geologic differences and handling inconsistency, there tends to be much variation among the size and shape of aggregates. V_{geology} is used as the term describing the variation to geology. It is a significant source of variation because it can change substantially with different geologies. V_{aggrpro} is the term given to the variation created by aggregate production because it is hard to crush all aggregates into specific percentage of gradation piles in aggregate production. $V_{\text{transport}}$, $V_{\text{stockpile}}$, and V_{loader} describe the variation of the aggregate due to different transport methods, different stockpile methods, and the loader operation. V_{coldfeed} characterizes the aggregates gradation change due to feed rate. In the production process, the quality of sampling and testing of aggregate can be inconsistent which may also produce variation and is termed $V_{s/t}$. Eq. (1) is a general equation to describe the gradation variation associated with each of the major aggregate process steps with e means undefined variation or error (Heitzman 2009)

$$V_{\text{aggr}} = V_{\text{geology}} + V_{\text{aggrpro}} + V_{\text{transport}} + V_{\text{stockpile}} + V_{\text{loader}} + V_{\text{coldfeed}} + V_{s/t} + e \quad (1)$$

Each HMA project can have different specifications from the client. For example, a highway requires a different asphalt mixture specification than a city road or a rural road. To meet these specifications, a JMF is developed for each project requirement. The JMF specifies the asphalt content and the aggregate gradation requirements to ensure a good quality pavement product.

Current quality control of HMA relies on samples taken from production, which are then analyzed in the lab to assess the actual gradation. The result is given to the HMA plant operator; however, the time required for testing is usually two to three hours. This long time lag sometimes can result in a significant amount of the HMA being produced out of specifications. For instance, a typical asphalt producer has a production rate of 100–300 tons/h. Because of the long analysis time it could produce 300–600 tons of poor quality product before the departure from specification is realized, resulting in either costly waste or substandard pavement at the job site. In fact, given the current practice of testing a very small proportion of

daily production, the actual amount of out of specification mix being produced cannot be gauged with any accuracy. Moreover, laboratory analysis of samples is expensive as special equipment and expertise are required. These important factors have motivated the development of an online process monitoring and control system.

Processing Model

The aim of this model is to make effective and timely production adjustments to the cold-feed bin proportions of aggregate in order for the HMA process to continuously adhere to the JMF specifications. The production process is modeled so that the relationship of outcomes with raw materials and process variables is quantified.

Input Data Collection and Analysis

The HMA production process is continuous, whereas simulation is primarily discrete event modeling. Many applications that discretize continuous systems have been presented in the literature. Among them, Fioroni et al. (2007) transform an ore conveyor transport system to a discrete model. Their system is very similar to the main conveyor belt that is used in hot mix asphalt production. They call the discrete units “blocks” and calculate weight of each by using the distance covered by the conveyor and knowing the velocity of the conveyor. Herein, the continuous flow along the conveyor is transformed into discrete blocks using a time step. One minute was chosen as the unit time step for this HMA production modeling. Hypothetically, if the discrete time units are small enough, the model resolution will increase until it approaches a continuous model.

As noted above, aggregate gradation can vary widely. It is assumed that the input data follows a Gaussian (that is, Normal) distribution whose parameters are the mean and standard deviation of the gradation percent passing each sieve. This distribution was chosen because it represents a wide variety of physical phenomena well and is robust to departures to exact adherence to the distribution. Data have been provided by the National Center for Asphalt Technology and, to better mimic conditions of real HMA plants, the model considers only the four most influential sieves. These are 3/8 in., No. 8, No. 30, and No. 200. The JMF requirements have three aspects; they are (1) production proportion of overall blend weight coming from each bin, (2) the upper/lower limits on combined sieve gradations, and (3) percentage of crushed, friction, and natural sand constraints.

Control Logic Model

The online process control model is established using commonly available software—ARENA discrete event simulation software, Visual Basic programming language, and Excel. ARENA is used to mimic a real HMA plant, that is, it creates a virtual environment in which to test and analyze the control system. Excel handles the gradation data arithmetic manipulation (which in this simulated environment is created, however, in a production environment the gradation data would come directly from sensors in the plant). Sensors of either line-laser or optical pattern recognition with cameras would monitor the gradation of aggregate from each cold-feed bin and transmit the data continuously to the Excel part of the system. Optimization algorithms are written in Visual Basic and govern the timing and method of control adjustments. Fig. 1 shows the logic of the online control model. Note that while ARENA operates in discrete time, a real plant operates in continuous time.

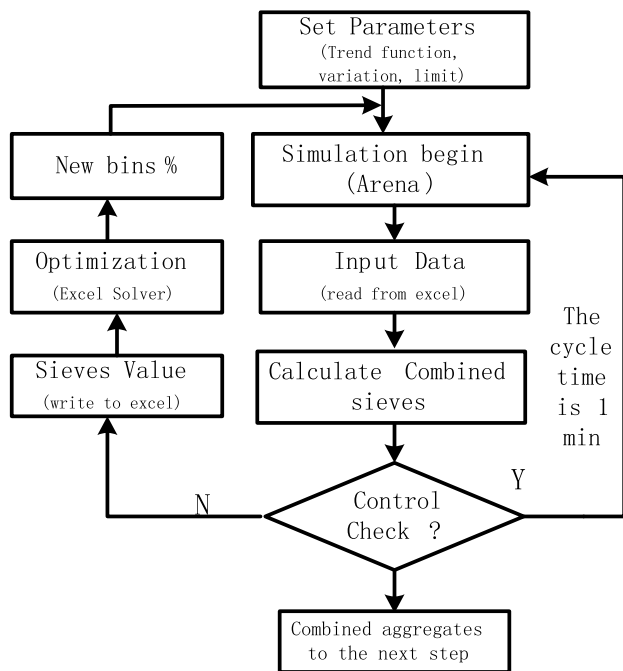


Fig. 1. The control logic of the model

As mentioned before, a discrete time slice of one minute has been chosen, which is close to continuous time.

To begin a virtual HMA operation, the user sets various parameters that would describe the plant situation to be mimicked including the aggregate gradation trend function, the aggregate gradation variation, the preferred control logic, and the moving average of percent aggregate passing each sieve. These are fully defined below. Then the model reads the moving averages of the percent passing each sieve from each of the five cold-feed bins from Excel, the simulation model begins to run and calculates the combined sieves gradation profile. If this gradation profile is “in control”, then there is no need for control action. On the other hand, if the gradation profile is “out of control”, then corrective action is taken. The corrective action is to reoptimize the blend by adjusting the proportion coming from each bin. The simulation continues to run until a specified termination criterion is met, which is 10 h (working time of a typical day) of simulation time in this paper.

In order to simulate a real production process, the trend function and variation of the aggregate are set in the simulation model. The trend function describes a possible change in aggregate gradation over time. Three trend functions are investigated (see Fig. 2). These are an alternating step function, a linear increase over time, and a linear increase and decrease over time.

The variation of aggregate gradation in each bin is specified by the Gaussian distribution standard deviation. Medium and high levels of aggregate variation are considered in this paper.

The gradation control limit triggers when control action is taken. The system has two alternatives for the triggering limit specification—the production control has a limit that is tighter than the JMF specification limit. The user selects either the JMF specification limit or the tighter production limit. The former would ensure mix would meet the specifications, but the latter would produce an even better product with less variability.

The main question for the system control logic is, “Is the system in control?” The concept of “in control” is defined by the policy selected by the user. There are four different control policies used

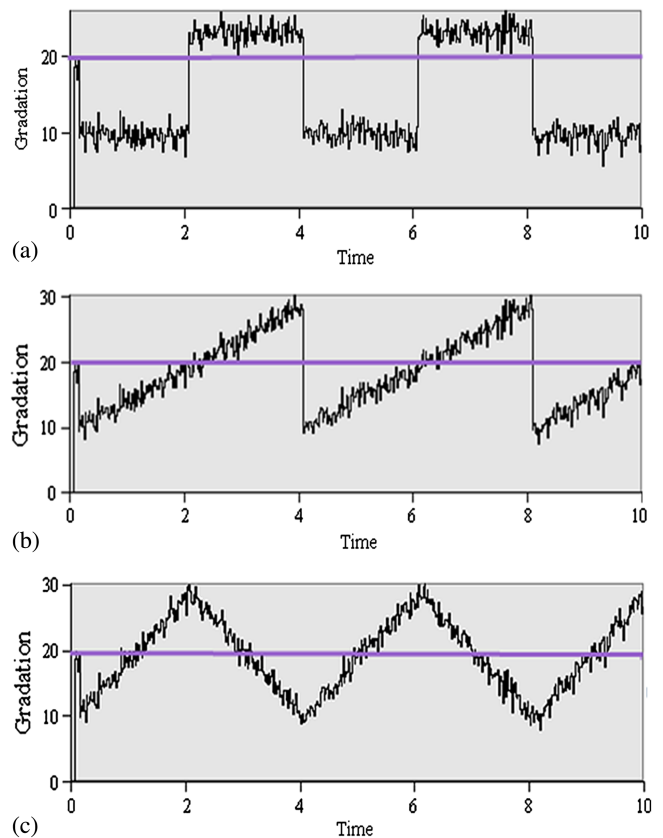


Fig. 2. Three kinds of typical trend function: (a) trend 1—alternating step function; (b) trend 2—linear increase; (c) trend 3—linear increase and decrease

in this paper (besides the No Control policy as the baseline) from which the user selects:

1. Control 1: If any combined gradation of any sieve goes beyond the control limits (specified as either specification control or production control) the proportion of aggregate contributions of bins are reoptimized;
2. Control 2: If any combined gradation of at least two sieves goes beyond the control limits, the proportion of aggregate contributions of bins are reoptimized;
3. Control 3: If the total gradation deviation is beyond 70% of the maximum allowable deviation (the total upper and lower limit of four sieves), the proportion of aggregate contributions of bins are reoptimized; and
4. Control 4 (combination of controls 1 and 3): If any combined gradation of any sieve goes beyond the control limits or is beyond 70% of the maximum allowable deviation, the proportion of aggregate contributions of bins are reoptimized.

In order not to overreact to sporadic changes in gradation with control actions, the moving average of the gradation values from each bin are used. This smooths the data and reduces the chance that a control action will be initiated for only a single out-of-control event. A moving average windows of 4 and 8 are considered. The system was initially run without a running average, but the natural variability of the process triggered too many adjustments and resulted in overall poor process improvement.

Optimization Model

In this paper, the optimization model builds on the algorithm of Kabadurmus et al. (2010). When the system is triggered as being

out of control, the optimization model will reoptimize the percentages from each bin in the mix to bring the overall gradation profile back within specifications. The optimization objective is to minimize the total deviation of the blended gradation from the JMF gradation over all sieves. The optimization algorithm is defined as

$$\min \sum_j D_j D_j = \frac{|n_j - \sum_i x_i g_{ij}|}{(r_j^{\max} - r_j^{\min})/2} \quad (2)$$

$$\text{s.t. } b_i^{\min} \leq x_i \leq b_i^{\max} \quad (3)$$

$$r_j^{\min} \leq \sum_i x_i g_{ij} \leq r_j^{\max} \quad (4)$$

$$c_p^{\min} \leq \sum_i x_i a_{ip} \leq c_p^{\max} \quad (5)$$

$$\sum_i x_i = 1 \quad (6)$$

$$x_i \geq 0 \quad (7)$$

where i is each cold-feed bin, j is each sieve, D_j is the total deviation, n_j is the JMF target on sieve j , x_i is the proportion of bin i in the overall aggregate blend, g_{ij} is the sieve j value from bin i , a_{ip} is the aggregate property p value from bin i , (b_i^{\min}, b_i^{\max}) is the upper and lower limits of bin i optimum feed rate range percentages, (r_j^{\min}, r_j^{\max}) is the upper and lower control limits of sieve j , and (c_p^{\min}, c_p^{\max}) is the upper and lower limits of the aggregate property (crushed, natural sand, and friction) proportion.

Eq. (2) is the objective function of the optimization model to measure the total deviation from a target over all bins and all sieves. Eq. (3) is the constraint of upper and lower limits of the bin feed rate expressed as percentages. Upper and lower control limits of the gradations of sieves are stated in Eq. (4). Proportion crushed, friction and natural sand constraints of the aggregate are stated in Eq. (5). The summation of all aggregate proportions must be 1, and each of them must be nonnegative as are stated in Eqs. (6) and (7). Taken together these equations specify a straightforward optimization problem that is readily solvable by Excel Solver.

Implementing this optimization algorithm is a bit more complicated because of the real-time nature of HMA production. Aggregates are stored in bins and moved to the main conveyor from those bins, therefore conveyor speed impacts combination of the aggregates. If the distance between any two bins is identical the travel time from bin i to bin $(i + 1)$ is also the same (where $i = 1, 2, 3, 4$). If the percentages of aggregate from all bins are changed simultaneously, variations in the overall weight of the final product will result because of the different times when the aggregate will enter the conveyor belt from the five bins. To overcome this problem, the blend must be changed sequentially. First, the amount of aggregate from bin 1 is changed (because it is farthest from the drum), then after the time it takes the aggregate from bin 1 to move to bin 2, bin 2's amount of aggregate is changed. The same procedure happens for bins 3–5.

The Simulation Model

This section describes the software system in more detail. Fig. 3 shows a sample screen shot of the user interface where the user will select the parameters of the virtual environment (the trend function, the moving average window, and the variation) and the control policy (the control action rules and the triggering limit).

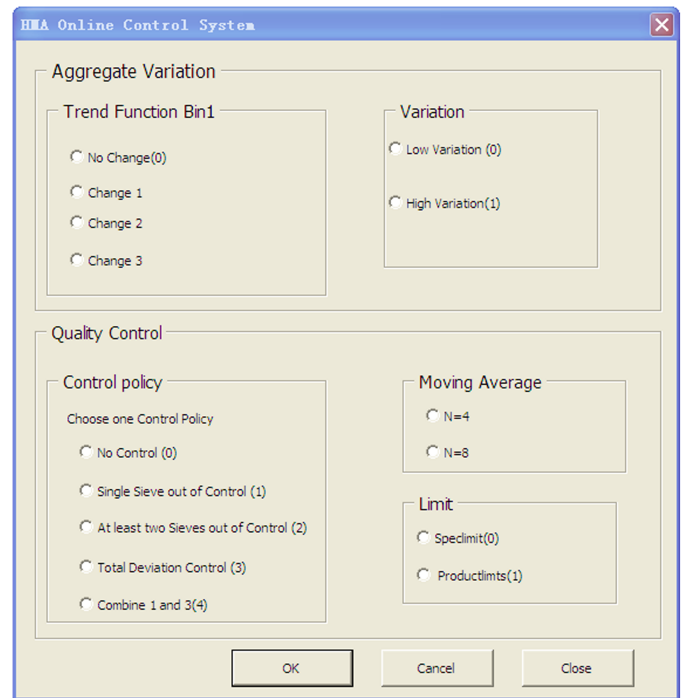


Fig. 3. The user input screen to create the virtual environment

Input Data and Parameters

The input data to test the system was provided by the National Center for Asphalt Technology. These data represent commonly observed data from operations of hot mix asphalt plants and a typical JMF with associated specification and production limits. The data are composed of four parts (see Tables 1 and 2). The first part is the mean and standard deviation of the gradation of each sieve from five bins. These values are expressed as percentages that go through the sieves and are shown in Table 1. The standard deviation values are similar to the values reported by Turochy et al. (2006) and Turochy and Parker (2007). The second part is the Job Mix Formula and the upper and lower limits for either specification or production. As mentioned earlier, the production limit is tighter than the specification limit. These are shown at the lower rows of Table 1 and indicate the \pm values allowable from the JMF target. The specification tolerance limits are generally wider than \pm two standard deviations of normal production variation, but will trigger

Table 1. The Aggregate Input Data and Specifications

Aggregate criteria	Bins	Sieves			
		3/8 in.	Number 8	Number 30	Number 200
Mean of gradation	1	52	14	7.9	3.7
	2	100	96	51	14
	3	100	86	41	1.4
	4	100	7	1	0.1
	5	100	52	9	0.7
Standard deviation of gradation	1	3.00	2.00	1.00	1.00
	2	0.00	1.00	4.00	2.00
	3	0.00	2.00	3.00	0.50
	4	0.00	1.00	0.50	0.50
	5	0.00	3.00	2.00	0.01
JMF sieves target percentage		82.20	33.00	14.30	3.50
Specification limit tolerance		8.00	5.00	4.00	2.00
Product limit tolerance		5.00	4.00	3.00	2.00

Table 2. The Aggregate Initial Data and Limits

Bin	Initial proportion	BIN capacity range percentage	
		Minimum	Maximum
1	37	17	57
2	14	5	23
3	7	2	12
4	30	10	50
5	12	5	23

noncomplying gradation when the bin gradation trends in Fig. 2 are added. The initial percentages from the JMF and the upper/lower limits of the five bins are in Table 2. The percentage from each bin during production must be between its upper/lower limit, and this constrains the process optimization procedure. The fourth part is the characteristics and upper and lower limit of each aggregate property for each bin, and this is in Table 3. Crush is the percentage of the aggregate that was produced by crushing. Friction is the percentage of aggregate that has required friction properties. Sand

Table 3. The Aggregate Properties and Limits

Bin	Crush	Friction	Natural sand
1	100	80	0
2	100	0	0
3	100	0	0
4	100	0	0
5	0	0	100
Maximum	100	50	16
Minimum	80	20	5

is the percentage of aggregate that is from a natural sand deposit. The specification limit maximum and minimum values of these components for the entire mix (a weighted average over the five bins) are shown at the bottom of Table 3.

During operation of the system, the user is provided with graphic displays that show various metrics over time. Fig. 4 shows representative graphs produced by the system.

Computational Experience and Results

Different scenarios were considered in the virtual plant to ascertain which combination of control logic, moving average window and control limit is superior, and to quantify the effects of the system relative to an uncontrolled system. Results are obtained by a single run of a simulated 10 h (600 min), which is equivalent to one working day of a typical HMA production plant. Fig. 5 shows the typical simulation results. In the right column, “# out of spec” means how long (in min) the system is out of specification limits, where the maximum is 600 min (the 10 h of simulation time). “# blend changes” indicates the number of optimization responses to when the system is out of control according to the control logic. “# no solution” means the number of times that the optimization component (Excel Solver) cannot find any feasible solution (this was very rarely experienced). “Sieve1Deviation, Sieve2Deviation, Sieve3-Deviation, and Sieve4Deviation” means the deviation from the JMF target for the different sieves. “AllSieveDeviation” is the summation of the deviation values (over time) of all sieves using Eq. (2), which defines deviation as a percentage between the target and specification limit value of the corresponding sieve.

In this case, there were 23 times that the optimization algorithm reformulated the percentage from each bin (# blend changes at right in the figure) during the 10 h (600 min) of simulation. The mixture

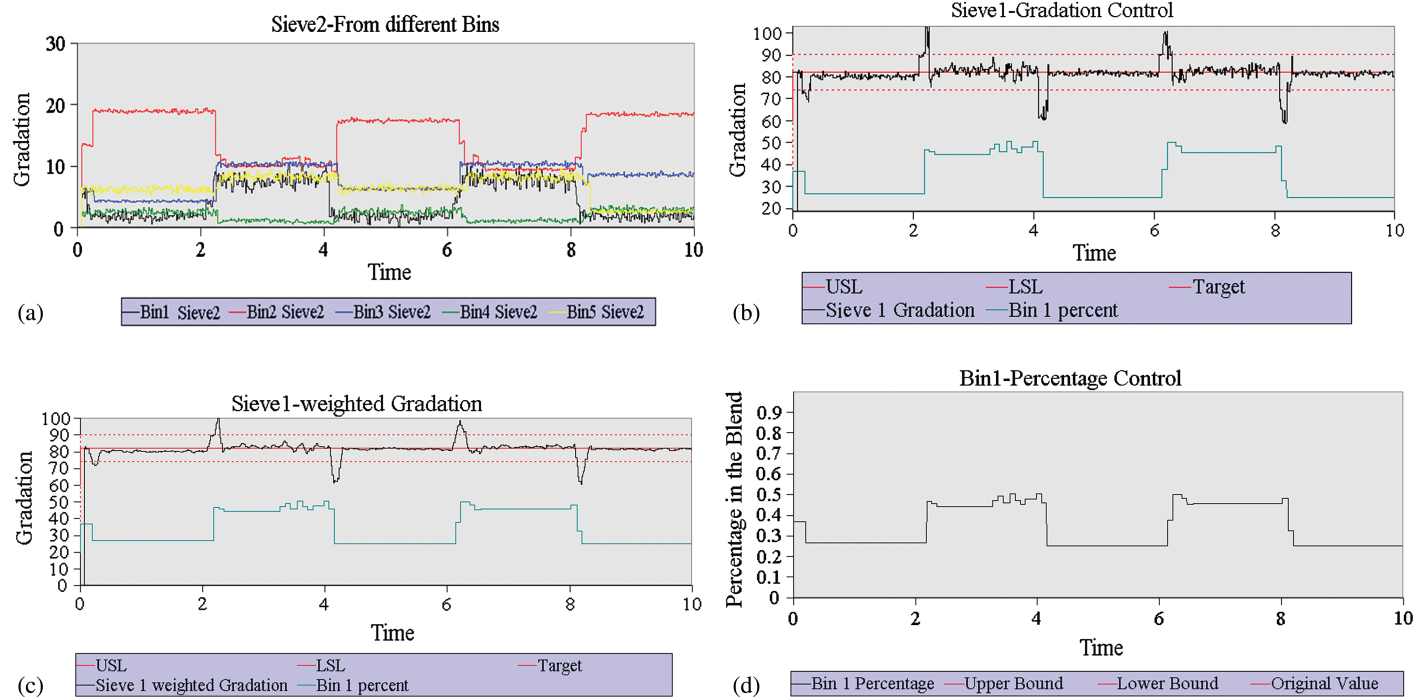


Fig. 4. (Color) Sample plots provided during operation of the virtual HMA plant: (a) gradation of sieve 2 from all five bins (each bin is shown as a different color) over time; (b) the gradation of sieve 1 from all bins (top) with bin 1 percentage of the mix (bottom); this shows as gradation changes, the bin proportions in the mix change; (c) data from (b) (above) after using the moving average smoothing; (d) the proportion from bin 1 in the mix over time; the control logic has altered the proportion from bin 1 to respond to changes in gradation; the allowable values of bin 1 proportion are from 17 to 57% (see Table 2)

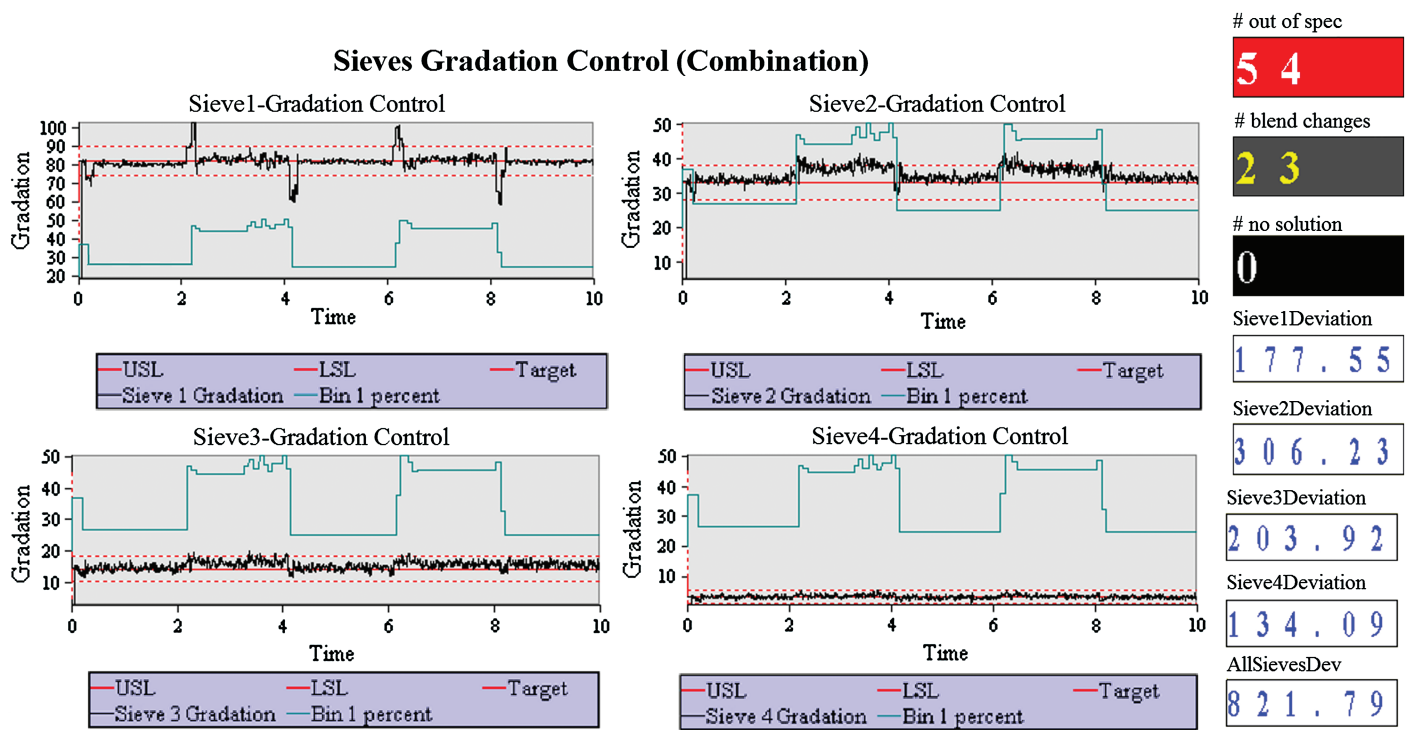


Fig. 5. (Color) Typical simulation results; over a 10-h day, the mixture from each bin was altered 23 times and this incurred an out of specification total time of 54 min (2.35 min per reoptimization trigger); the x -axis is in units of hours

was out of specification for a total of 54 min, that is each reoptimization took an average of 2.35 min to move the process back to within specification. This time is not the computational time (which is almost instantaneous) but rather the time the physical process needed to fully absorb the bin percentage adjustments to reach JMF target again.

The behavior of the simulated production environment and the efficacy of alternative control policies were examined through a full factorial experiment. The experiment had the following five factors with different levels: (1) control policy with four levels (defined in an earlier section), (2) moving average window length with two levels of either four or eight time steps (min), (3) limit of production control with two levels of either Specification (looser) or Production (tighter), (4) aggregate variation in Bin 1 with two levels of either the stated standard deviation from Table 1 (medium variability) or 1.5 times that standard deviation (high variability), and (5) trend function of Bin 1 with three levels (defined in an earlier section). This results in 96 simulated days and the No Control policy is chosen as the baseline. The first three factors are those that need to be set by the user to obtain the best control possible for the HMA plant. The latter two factors are characteristics of the aggregate and cannot be controlled by the user. Note that the system was analyzed conservatively by allowing only the aggregate in the first bin to drift over time according to the trend function and to experience increased variability. The aggregate in the other four bins remained at their stated Gaussian distribution about the input bin gradation throughout the simulation. Had other bins also experienced drift and/or increased variation, more control actions would have been triggered and the process improvement would have been even greater than that discussed below.

Table 4 summarizes the results of the full factorial experiment. The percent reduction deviation is the reduced deviation from the control policy over the No Control baseline policy. The cells with

bold text are the best control policies for various scenarios, whereas the cells with italic entries are the combinations of best control policy, moving average window size, and control limit.

Control policies 1, 3, and 4 are effective in reducing the amount of deviation. Control policy 2 is too restrictive to positively impact production consistently. Control 1 reoptimizes the system when one sieve is out of control, but control 3 is focused on total deviation, which means it starts to reoptimize when the total deviation is larger than a set allowance deviation. Control 4 combines 1 and 3 and will reoptimize when one sieve is out of limit or the total deviation is beyond 70% of the max deviation. Which control policy is most effective depends on the trend characteristics of the aggregate. For trend functions 1 and 2, control policy 3 is best, but for trend function 3, control policy 4 is best. However, all control policies (with the exception of 2) are consistently effective relative to the baseline of No Control.

The simulations show that a moving average window value of four time steps is more effective than that of eight time steps when coupled with the production control limit. Eight oversmooths the data and makes the system less responsive to changes in the aggregate when using the production control limit. The production control limit is effective in forcing the system to reoptimize before the specification control limit is reached.

In summary, a choice of production control limit with a moving window of four time steps and a control policy of either 3 or 4 results in the best production outcomes (minimizing total deviation from the JMF target). However, almost regardless of control choice, overall production improvements by using this system were on the order of 20–40% reduction in deviation from the job mix formula. This improvement was realized despite considerable variation over time in the aggregate gradation.

Table 4. Results of 96 Simulation Runs for the Full Factorial Experiment

Control policy	Moving average window	Control limit	Aggregate variation	Percent reduction deviation (%)		
				Trend 1 (%)	Trend 2 (%)	Trend 3 (%)
1	4	S	0	26.8	16.1	28.7
2	4	S	0	0.0	11.6	25.8
3	4	S	0	20.6	18.7	26.7
4	4	S	0	26.8	18.4	30.6
1	8	S	0	27.4	13.0	20.9
2	8	S	0	0.0	9.1	18.6
3	8	S	0	-2.6	13.0	22.4
4	8	S	0	27.4	14.5	24.0
1	4	P	0	20.2	18.2	36.0
2	4	P	0	0.0	19.2	28.7
3	4	P	0	30.5	20.3	28.6
4	4	P	0	20.2	18.5	39.1
1	8	P	0	21.5	17.6	30.9
2	8	P	0	0.0	13.8	19.6
3	8	P	0	24.2	18.9	29.1
4	8	P	0	21.5	16.0	34.5
1	4	S	1	20.4	9.1	28.6
2	4	S	1	0.0	8.1	21.5
3	4	S	1	17.7	14.6	24.1
4	4	S	1	21.2	15.2	30.9
1	8	S	1	18.0	11.0	19.6
2	8	S	1	0.0	1.1	12.8
3	8	S	1	1.9	10.0	21.5
4	8	S	1	18.0	11.0	22.2
1	4	P	1	18.1	18.5	35.0
2	4	P	1	-21.5	16.2	29.0
3	4	P	1	23.1	16.2	28.0
4	4	P	1	18.1	16.7	36.8
1	8	P	1	17.8	11.4	28.5
2	8	P	1	-12.7	13.1	20.2
3	8	P	1	23.2	10.0	28.1
4	8	P	1	17.8	11.4	30.4

Note: S = specification control; P = production control.

The improvement came about purely by changing the proportion from each bin and did not require any alteration to the aggregate itself. Also, these improvements occurred when only one bin (#1) experienced systematic change in the aggregate gradation. Had changes occurred over multiple bins, the process optimization module would have been invoked more often and would have resulted in even greater overall percent reduction in deviation compared to the No Control policy.

Conclusions

This paper described a unique real time online control system for hot mix asphalt production. The computational components are a discrete time stochastic simulation engine, a data processing platform, and an algorithmic optimization module. Most of the difficulty in reliably producing hot mix asphalt can be attributed to the fluctuation in gradation and the current inability to rapidly identify and compensate for such fluctuation. This system addresses this issue by monitoring and adjusting, as needed, the proportion from each cold-feed bin of aggregate during production. This is a key idea because instead of relying on improved aggregate

standardization and handling at the production site, the system accommodates the aggregate as it is.

While still immature, this simulation/optimization approach is practical and, as the computational results show, quite effective in reducing out-of-control mix being produced. It does not rely on significantly time-consuming laboratory testing. There is real potential to provide online control for plants to both improve the manufactured mix and reduce the HMA company's testing expenses. This software system coupled with either a line-laser imaging system or cameras with optical pattern recognition software would make a complete real time process improvement system that would be effective and practical.

There are opportunities to improve and refine the software system. Currently the system reacts to aggregate that departs from expected (that is, differs from the assumed distribution). An enhancement would be to predict aggregate changes a few time steps in advance. This would reduce the out-of-control time, as corrective action could be taken before the bin reached an out-of-control situation. More sophisticated control strategies could be developed and could be customized to the type of aggregate and the JMF at a specific manufacturer. This would be a relatively easy change computationally but might take significant development work to choose rules and algorithms that are particularly effective for the given scenarios.

Acknowledgments

This work was supported in part by the U.S. Department of Transportation, Federal Highway Administration.

References

- Brown, E. R., Kandhal, P. S., Roberts, F. L., Kim, Y. R., Lee, D., and Kennedy, T. W. (2009). *Hot mix asphalt materials, mixture design and construction*, 3rd Ed., NAPA Research and Education Foundation, Lanham, MD.
- Douglas, K. D., Coplantz, J., Lehmann, R., and Bressette, T. (1999). "Part 3—Quality control/quality assurance—Evaluation of quality control/quality assurance implementation for asphalt concrete specifications in California." *Transp. Res. Rec.*, 1654, 95–101.
- Fioroni, M. M., et al. (2007). "Simulation of continuous behavior using discrete tools: Ore conveyor transport." *Proc., 2007 Winter Simulation Conf.*, S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, eds., Omnipress, Madison, WI, 98–103.
- Gopalakrishnan, K., Shashidhar, N., and Zhong, X. (2008). "Study of compaction in hot-mix asphalt using computer simulations." *World Acad. Sci. Eng. Tech.*, 15, 830–836.
- Guo, D., Zhou, W., Aimin, S., and Ruyue, B. (2009). "Application of uncertainty analytic hierarchy process method for asphalt pavement construction quality control in China." *Transp. Res. Rec.*, 2098, 43–50.
- Hall, K. D., and Williams, S. G. (2002). "Part 3—Quality assurance—Establishing variability for hot-mix asphalt construction in Arkansas." *Transp. Res. Rec.*, 1813, 172–180.
- Heitzman, M. (2009). "Development of a hot mix plant production process control system." *NCAT Draft Rep.*, National Center for Asphalt Technology, Auburn, AL.
- Kabadurmus, O., Pathak, O., Smith, J. S., Smith, A. E., and Yapicioglu, H. (2010). "A simulation methodology for online process control of hot mix asphalt (HMA) production." *Proc., 2010 Winter Simulation Conf.*, IEEE, New York, 1522–1533.
- Tsai, B.-W., and Monismith, C. L. (2009). "Quality control-quality assurance sampling strategies for hot-mix asphalt construction." *Transp. Res. Rec.*, 2098, 51–62.
- Turochy, R. E., and Parker, F. (2007). "Comparisons of contractor and state transportation agency quality assurance test results on mat density of

hot-mix asphalt concrete: Findings of multistate analysis." *Transp. Res. Rec.*, 2040, 41–47.

Turochy, R. E., Willis, J. R., and Parker, F. (2006). "Part 2—Quality assurance—Quality assurance of hot-mix asphalt: Comparison of contractor quality control and Georgia Department of Transportation data." *Transp. Res. Rec.*, 1946, 47–54.

West, R. (2005). "Development of rapid QC procedures for evaluation of HMA properties during production." *NCAT Rep.*, National Center for Asphalt Technology, Auburn, AL, 05–01.

White, G. C., Mahoney, J. P., Turkiyyah, G. M., Willoughby, K. A., and Brown, E. R. (2002). "Online tools for hot-mix asphalt monitoring." *Transp. Res. Rec.*, 1813, 124–132.